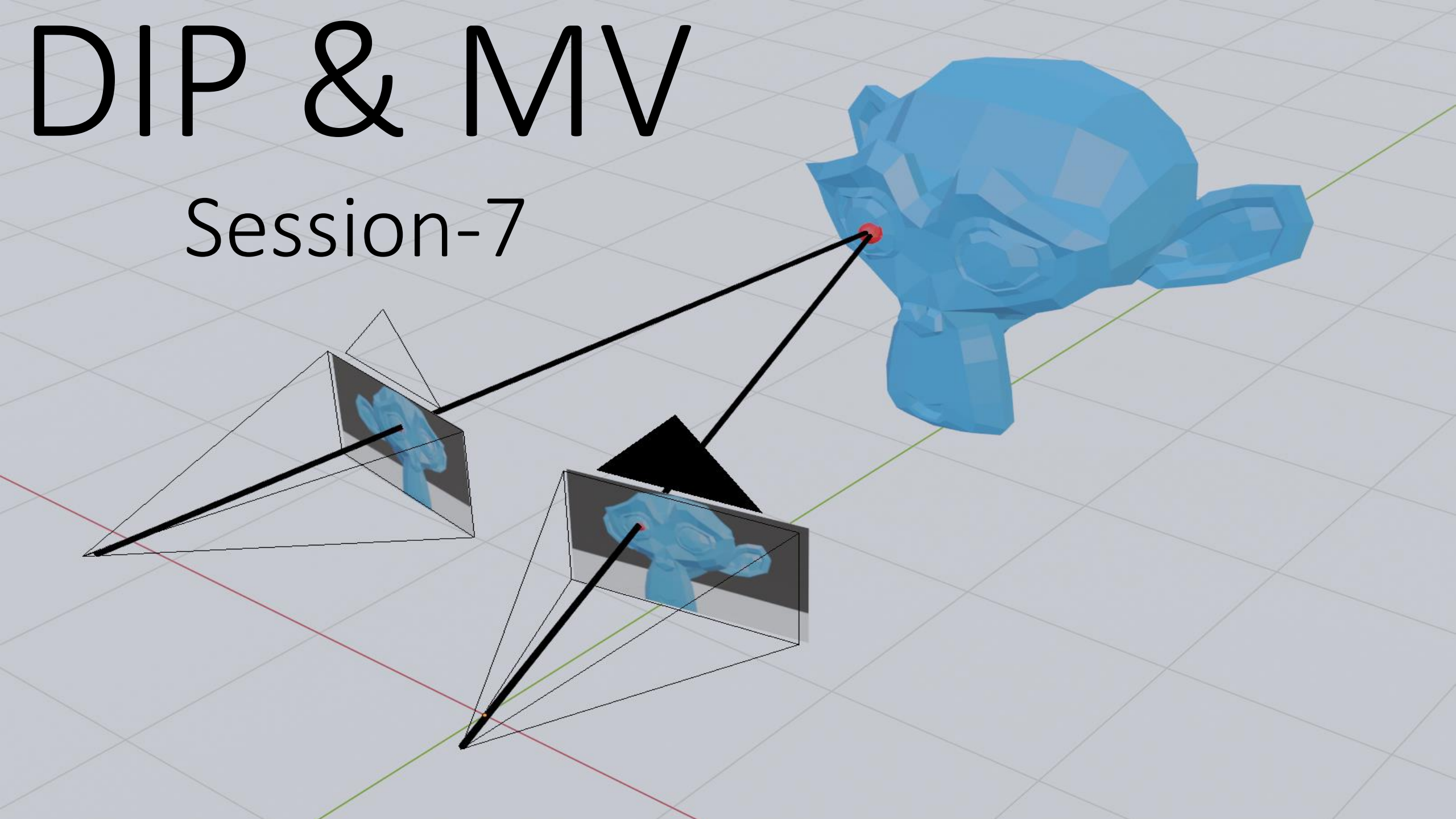
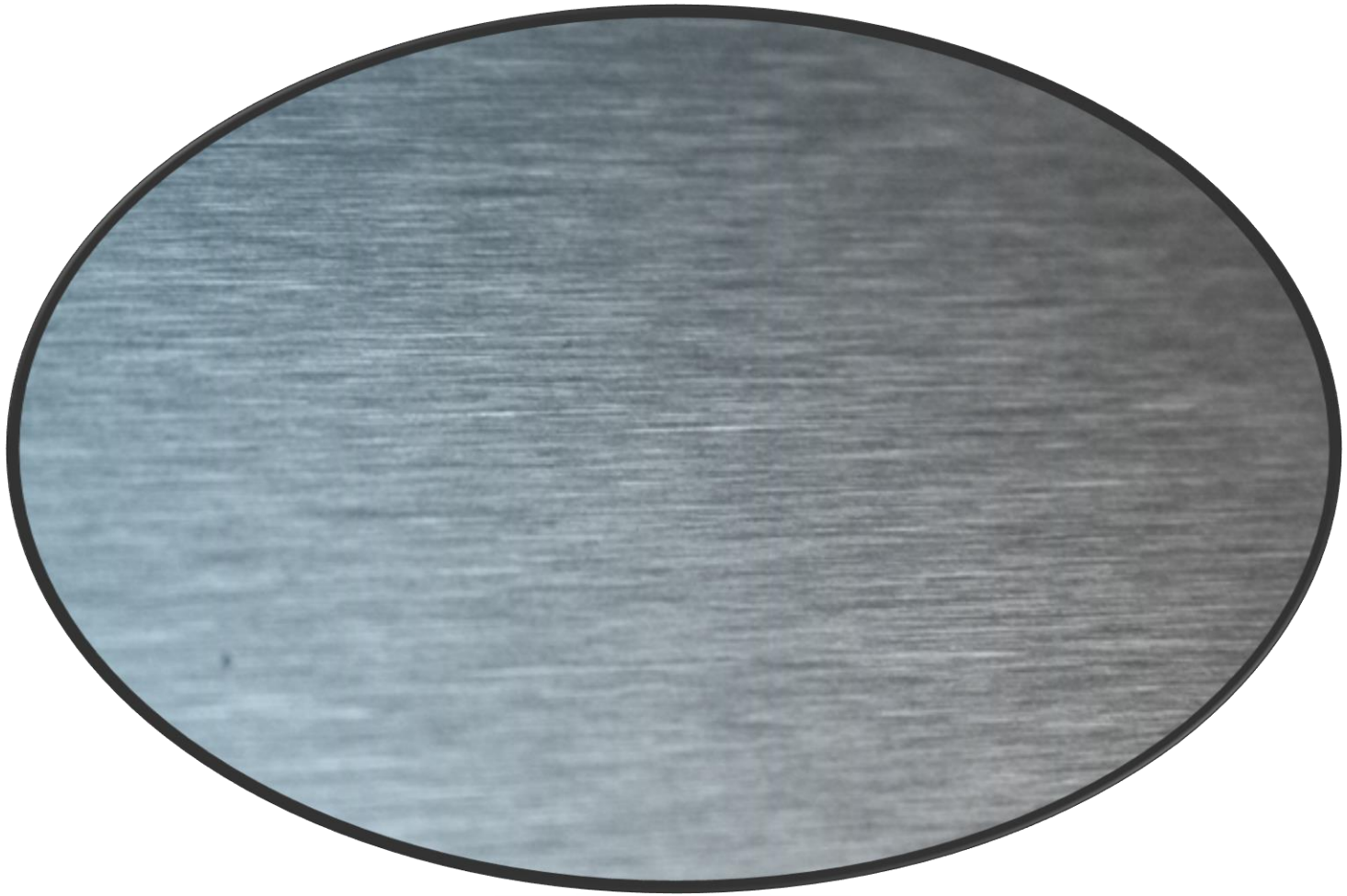
DIP & MV

Session-7



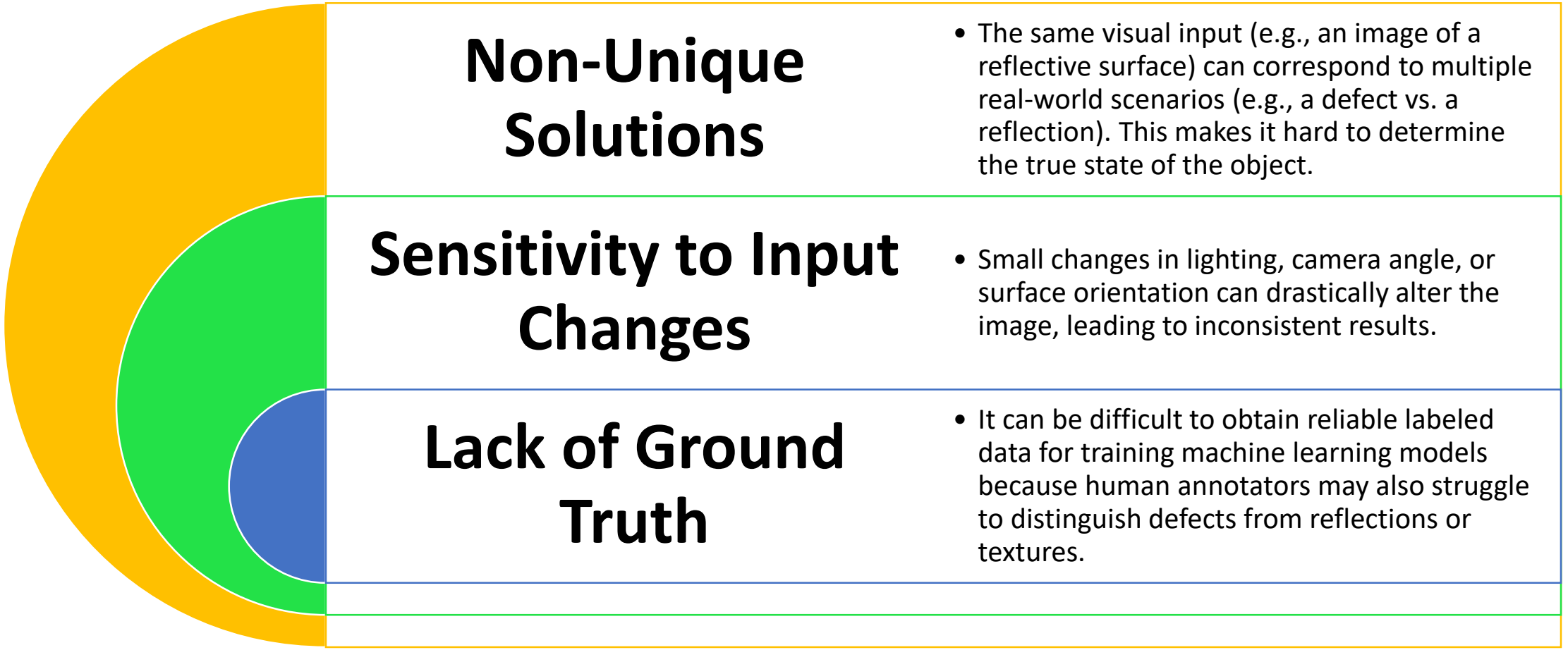
Class Activity # 01

1. Is the given scenario an ill-posed machine vision (MV) problem?
    a. If No, why?
    b. If Yes, what are the requirements to be an ill-posed problem?
2. What are the challenges for a MV system for this scenario?
3. How difficult is the scenario for human-based inspection?
4. What would be the ‘system’ requirements for MV system in case of:
    a. Product (or Manufacturing stage) inspection
    b. In-service inspection
5. What are the potential solutions to address the challenges you explored?
6. Which industries might benefit from your proposed solution?
7. What value addition your proposed solution(s) may suggest for any given industry of Pakistan?



panorama

Why It's Ill-Posed



Non-Unique Solutions

- The same visual input (e.g., an image of a reflective surface) can correspond to multiple real-world scenarios (e.g., a defect vs. a reflection). This makes it hard to determine the true state of the object.

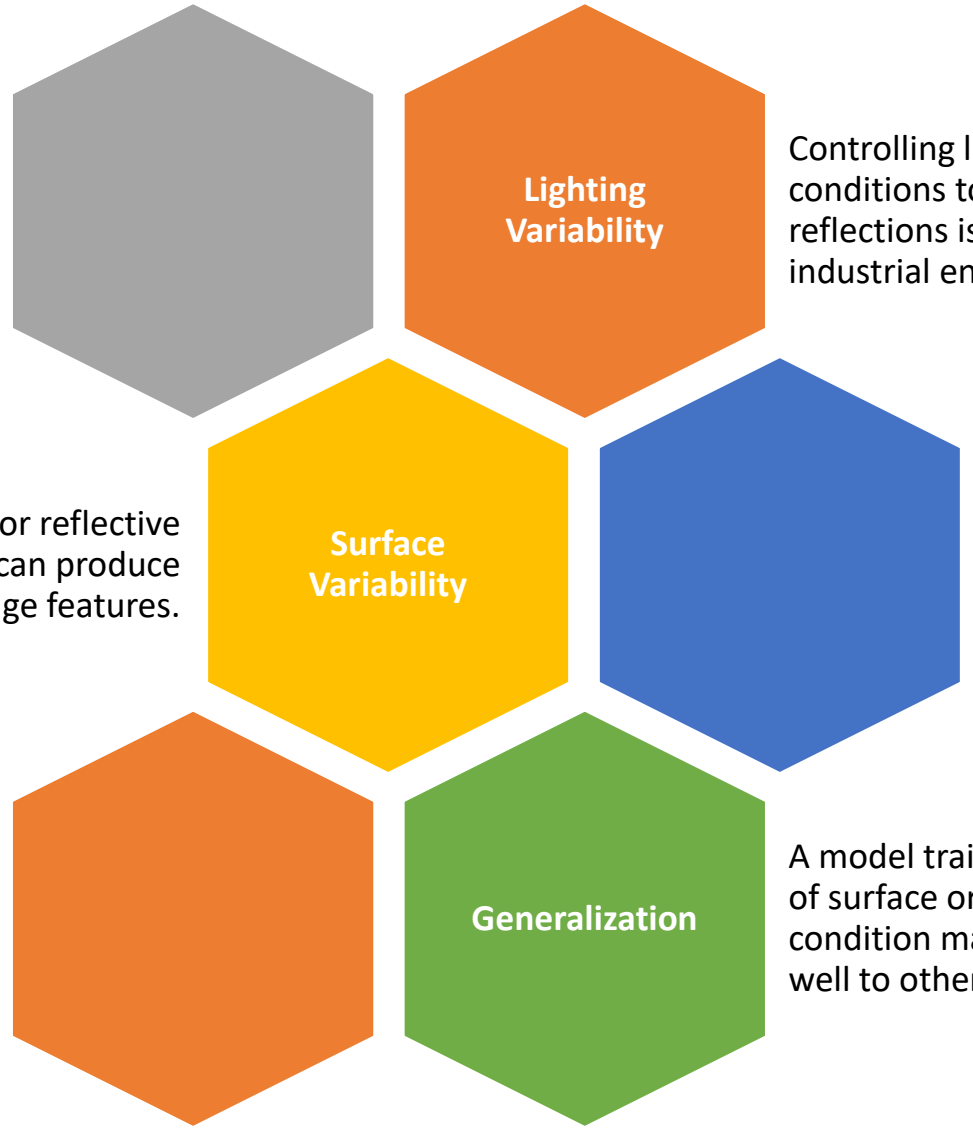
Sensitivity to Input Changes

- Small changes in lighting, camera angle, or surface orientation can drastically alter the image, leading to inconsistent results.

Lack of Ground Truth

- It can be difficult to obtain reliable labeled data for training machine learning models because human annotators may also struggle to distinguish defects from reflections or textures.

Challenges for a MV System



Controlling lighting conditions to minimize reflections is difficult in industrial environments.

Textured or reflective surfaces can produce inconsistent image features.

A model trained on one type of surface or lighting condition may not generalize well to others.

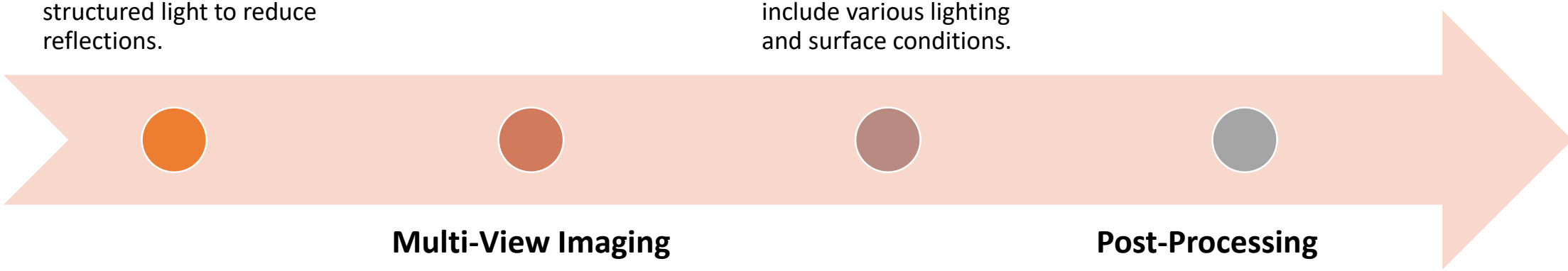
Candidates for Solution

Advanced Lighting Techniques

- Using polarized lighting or structured light to reduce reflections.

Deep Learning with Robust Datasets

- Training models on large, diverse datasets that include various lighting and surface conditions.



Multi-View Imaging

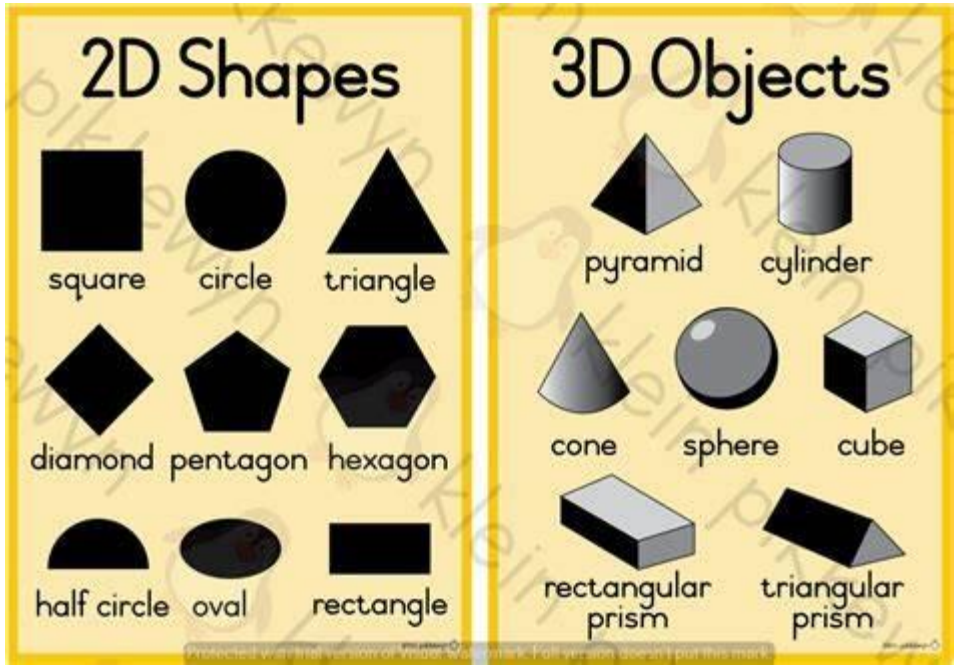
- Capturing images from multiple angles to disambiguate defects from reflections.

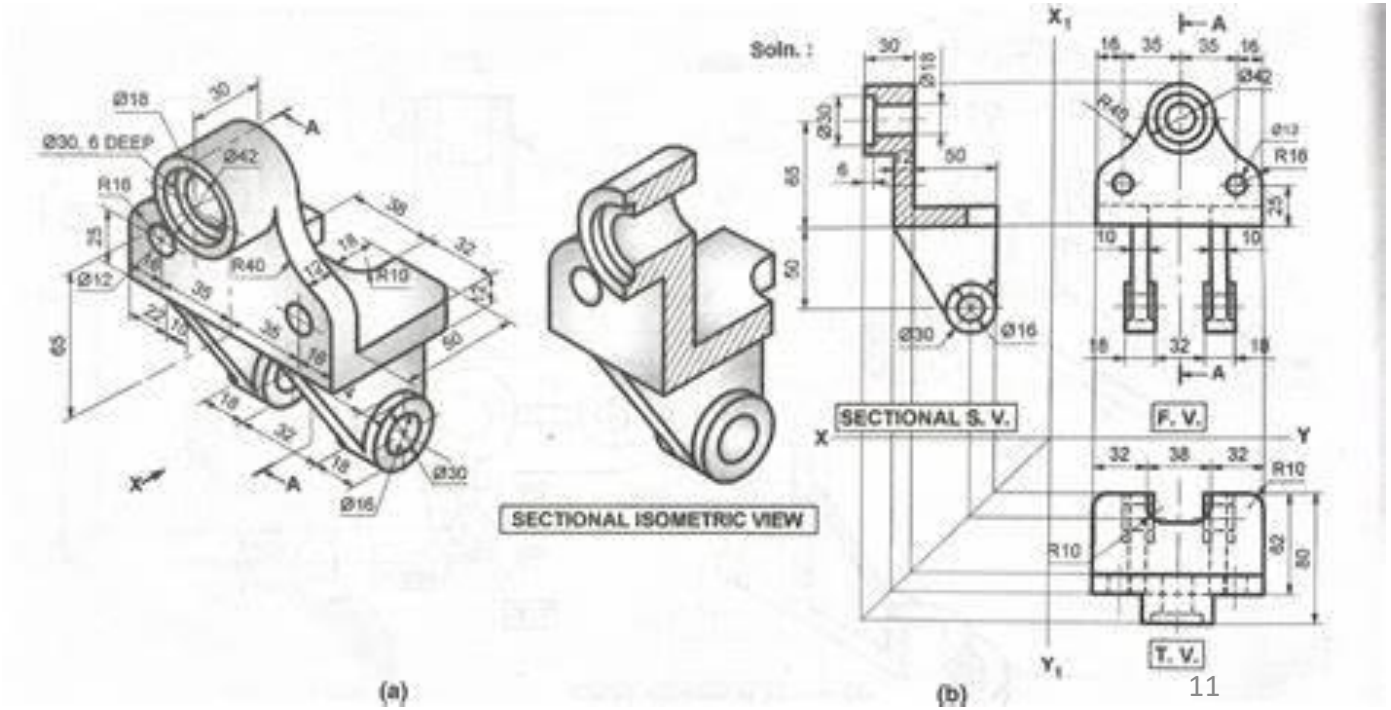
Post-Processing

- Using algorithms to filter out reflections or textures based on known patterns.

Class Activity # 02

- Given a single 2D image, the goal is to reconstruct the full 3D geometry of the objects or scene in the image. For example, estimating the depth, shape, and spatial arrangement of objects from a single photograph.





Why It's Ill-Posed?

Loss of Depth Information

A 2D image is a projection of a 3D scene, and depth information is lost during this process. Multiple 3D scenes can produce the same 2D image, making the problem underdetermined.

Ambiguity in Scale

Without additional context (e.g., known object sizes or reference points), it is impossible to determine the absolute scale of the objects in the scene.

Occlusions

Objects in the scene may occlude one another, making it difficult to infer the full 3D structure.

Lighting and Texture Ambiguities

Variations in lighting, shadows, and surface textures can make it challenging to infer shape and depth accurately.

Exercise

- A machine vision system is tasked with reconstructing the 3D shape of a piece of furniture (e.g., a chair) from a single photograph. The system must infer the depth, dimensions, and spatial arrangement of the chair's legs, backrest, and seat from a single 2D image.

Challenges

Infinite Possible Solutions

- Many different 3D configurations can produce the same 2D image, making it impossible to determine the "correct" solution without additional constraints.

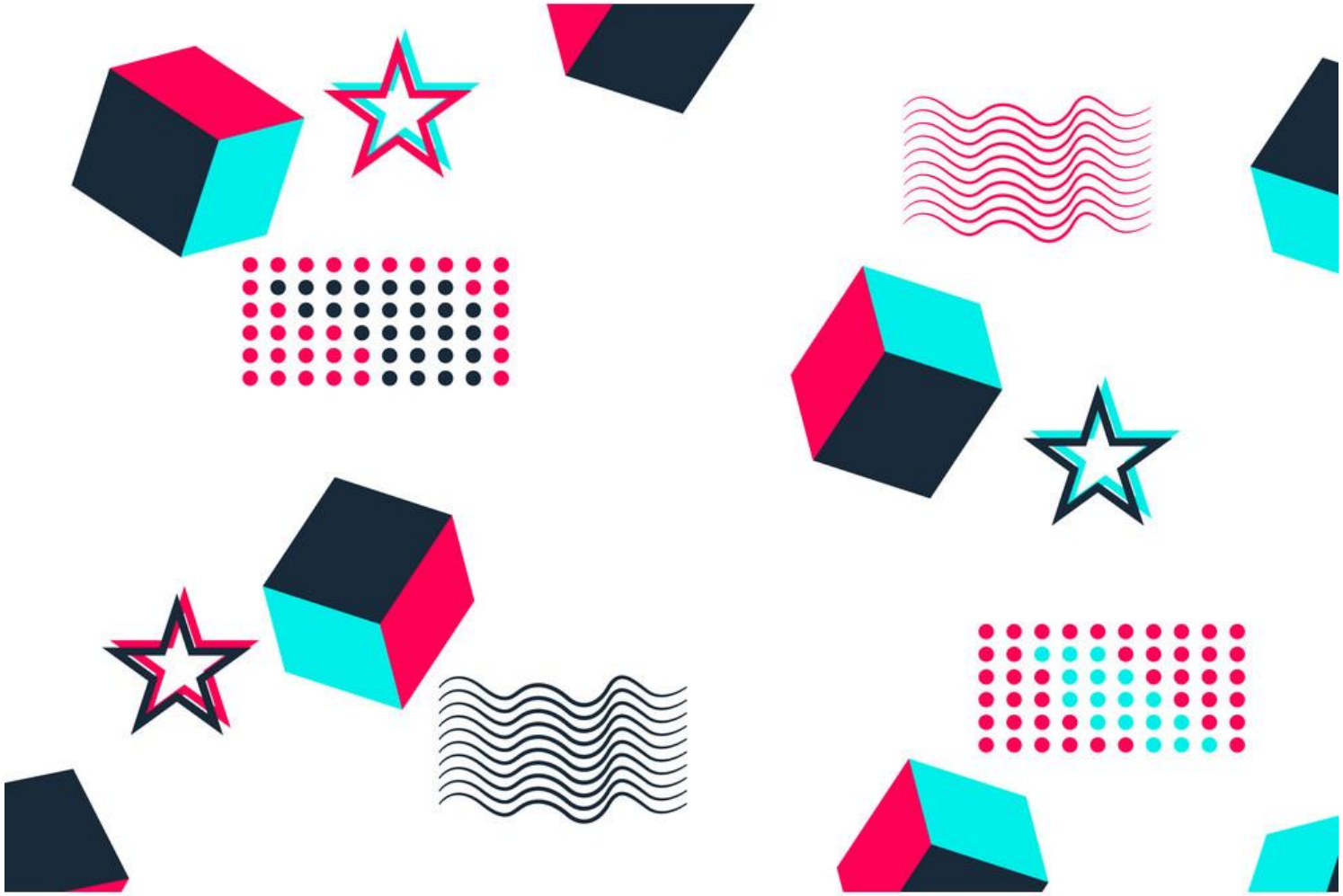
Lack of Ground Truth

- Obtaining accurate 3D ground truth data for training is often expensive and time-consuming.

Generalization

- A model trained on one type of object or scene may not generalize well to others.

Object with different backgrounds



Potential Solutions

Adding Constraints

Use prior knowledge (e.g., object shapes, sizes, or symmetries) to constrain the problem.

Multi-View Stereo

Use multiple images from different viewpoints to resolve depth ambiguities.

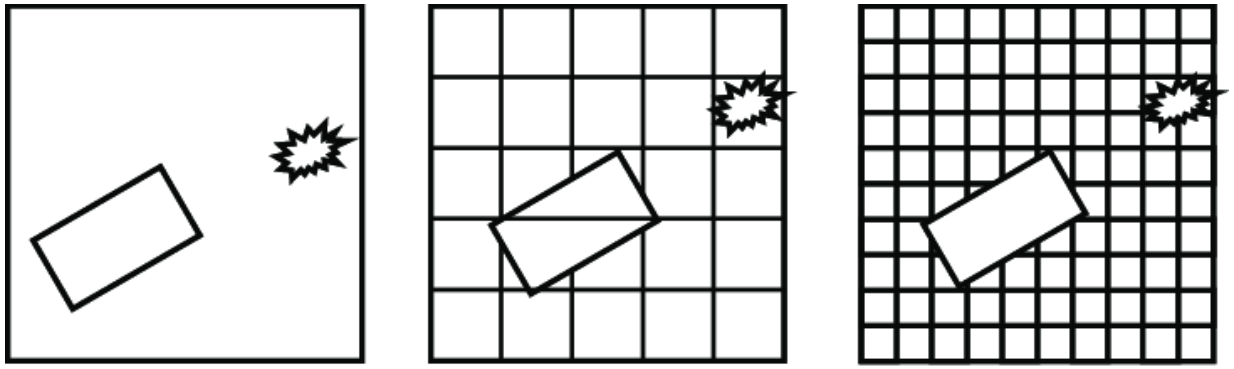
Deep Learning with Priors

Train deep neural networks to predict depth maps or 3D structures using large datasets and learned priors.

Structured Lighting or Sensors

Use additional hardware (e.g., LiDAR, structured light) to provide depth information.

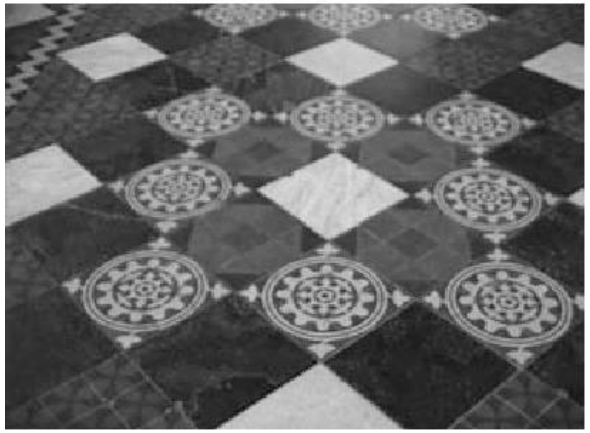
Object Scale Information



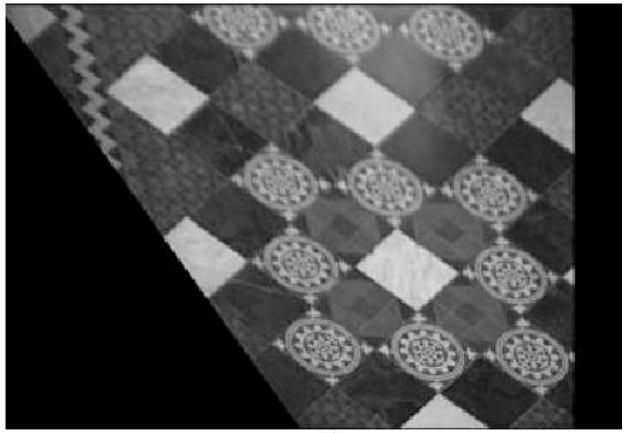
(a) 20 m pixel (b) 5 m pixel (c) 1.25 m pixel

Object Shape Information

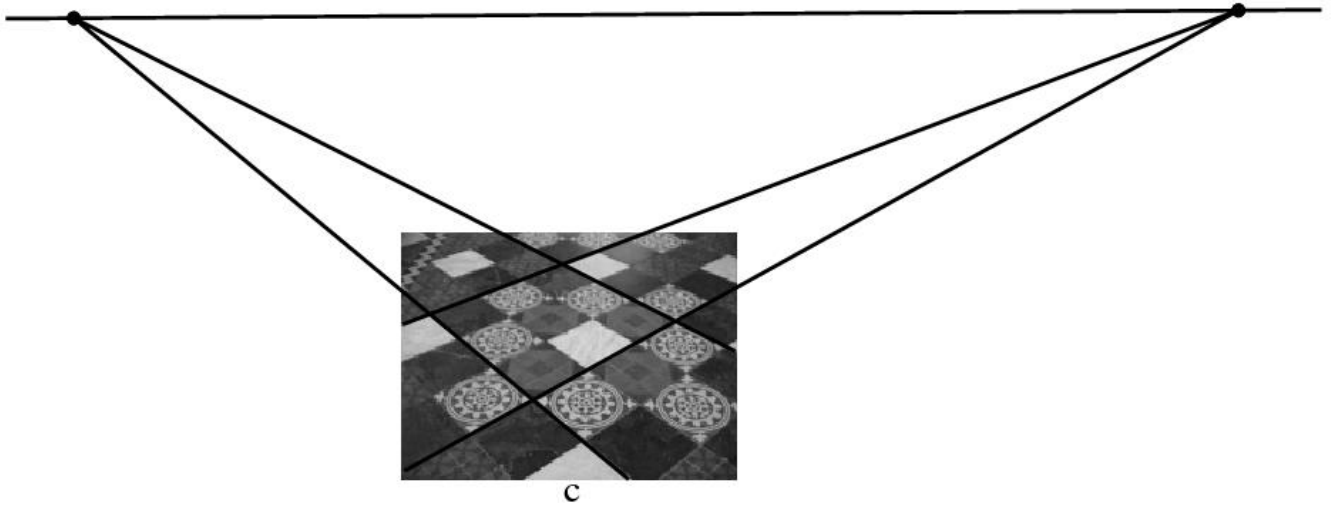
Multiple view geometry



a



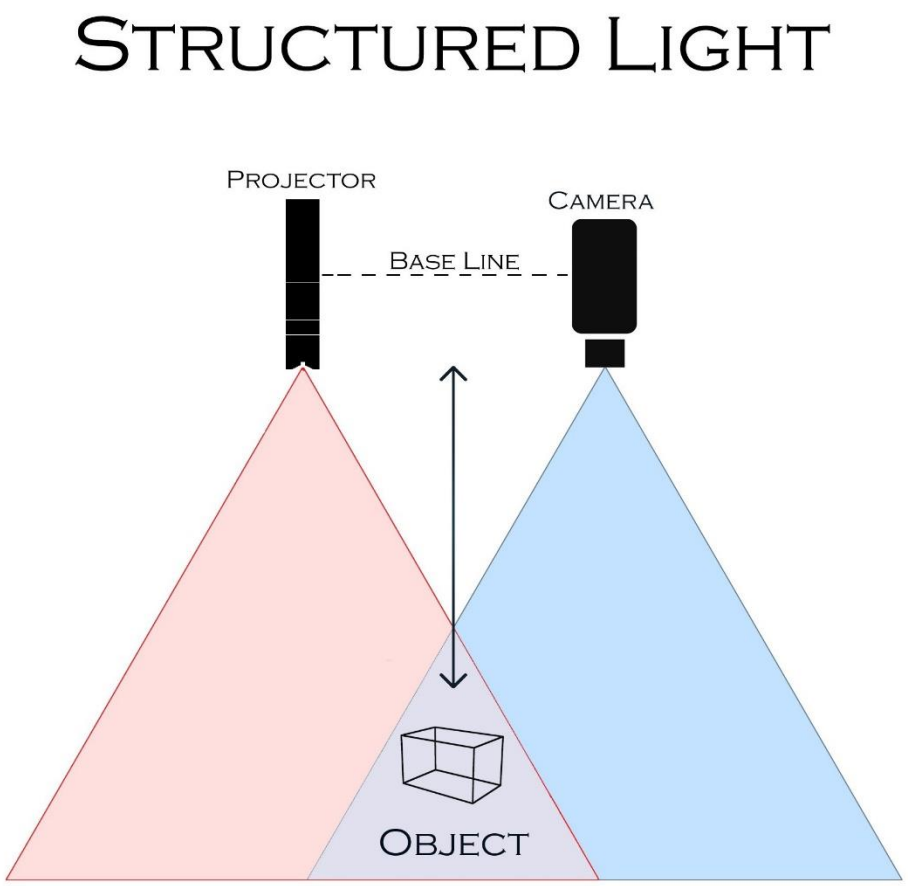
b

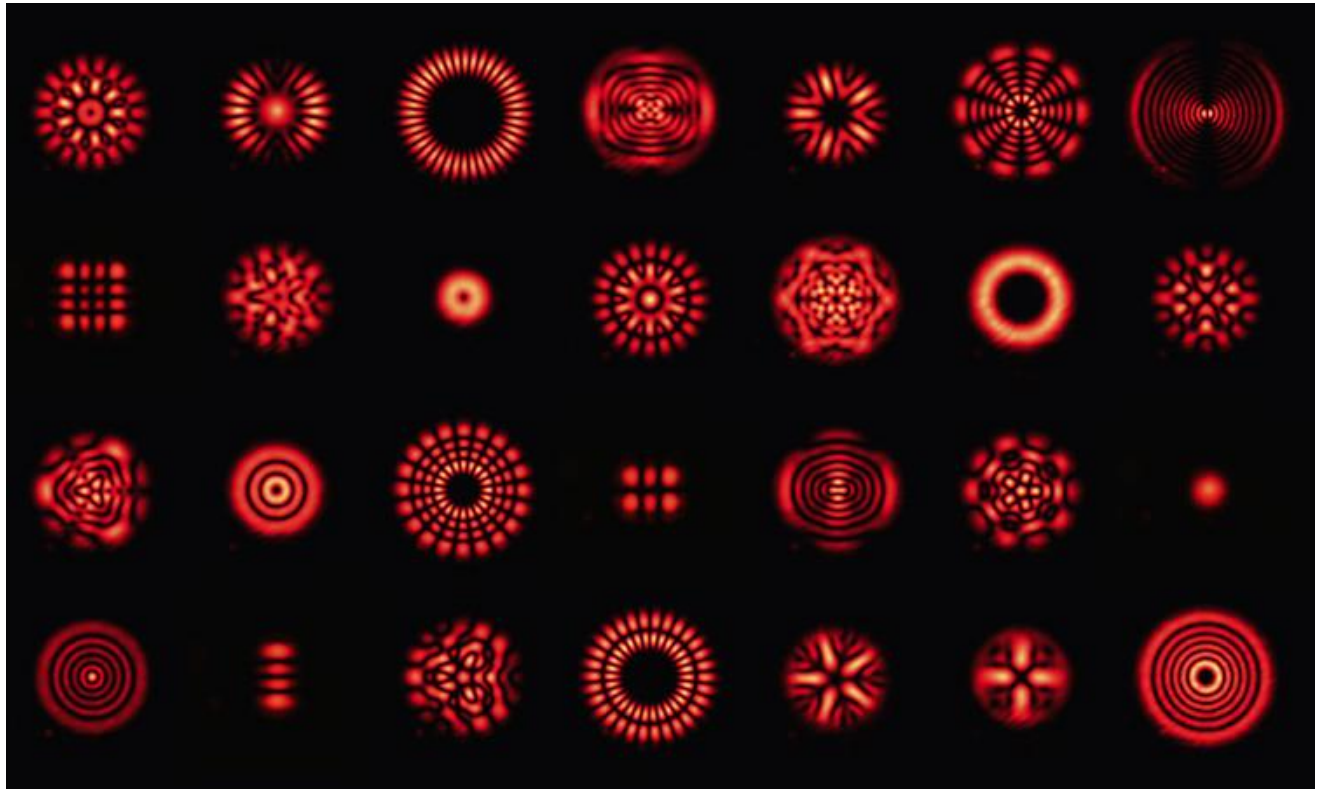


c

Structured Lighting

(Tailored for Purpose)





Class Activity-03

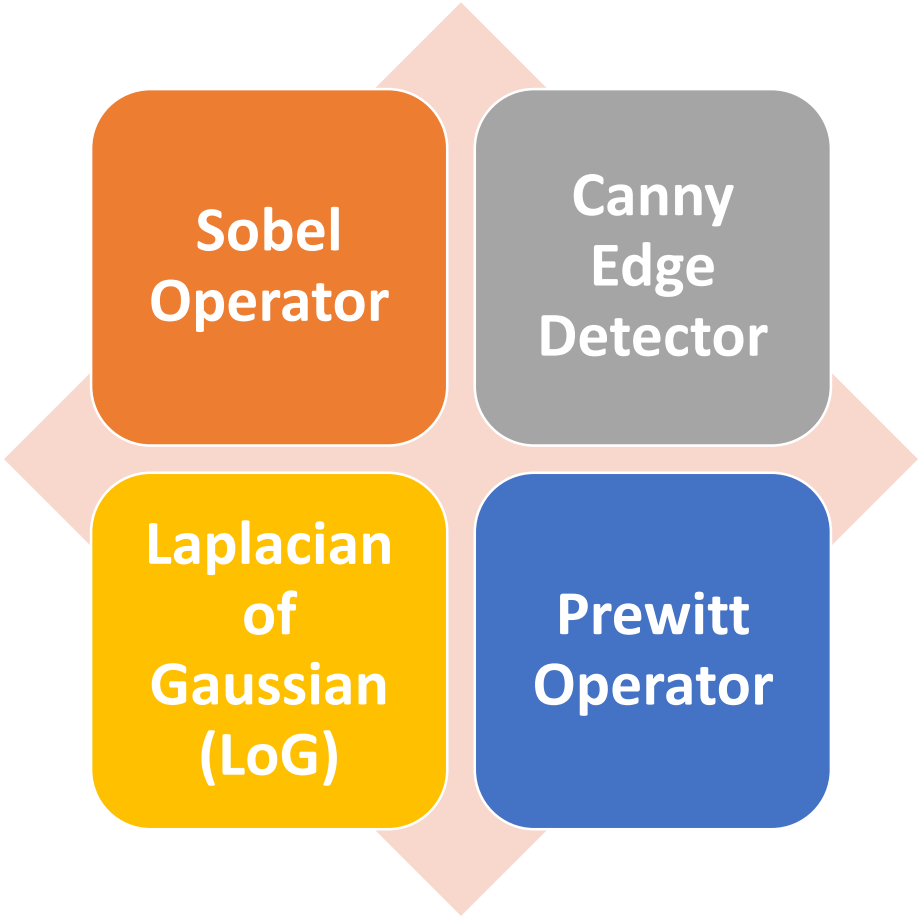
- Count the objects
- Count the categories
- Count each class(es) of categories
- Check which categories or classes may be misclassified

More on Edge Detection

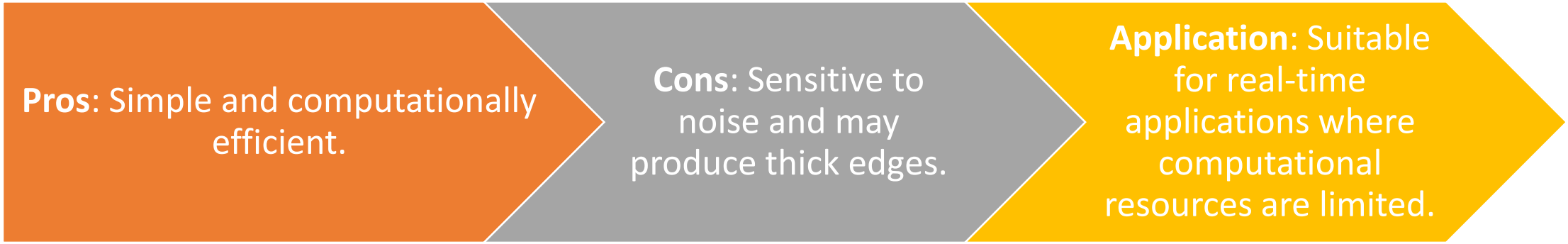
Edge Detection

- Edge detection is a fundamental technique in image processing and computer vision.
- It aims to identify the boundaries of objects within an image by detecting discontinuities in brightness.
- Edges are significant because they often correspond to important features in the image, such as
  - object boundaries,
  - surface markings, and
  - changes in material properties.

Edge Detectors



Sobel Operator


Pros: Simple and computationally efficient.
Cons: Sensitive to noise and may produce thick edges.
Application: Suitable for real-time applications where computational resources are limited.

Canny Edge Detector

Pros: Produces thin, continuous edges and is less sensitive to noise.

Cons: Computationally intensive.

Application: Ideal for applications requiring high accuracy, such as medical imaging.

Laplacian of Gaussian (LoG)

Pros: Effective in detecting edges at different scales.

Cons: May produce double edges and is computationally expensive.

Application: Useful in multi-scale edge detection tasks.

Prewitt Operator

Pros: Similar to Sobel but slightly less sensitive to noise.

Cons: Produces thicker edges compared to Canny.

Application: Suitable for general-purpose edge detection tasks.

Fill in the blanks

- **Edge Continuity**: _____detector outperforms others in producing continuous edges.
- **Noise Sensitivity**: _____ and _____ detectors are more sensitive to noise compared to others.
- **Computational Efficiency**: Sobel and Prewitt operators are more efficient, making them suitable for _____applications.

Canny Edge Detector, Prewitt, Sobel,

LoG (Laplacian of Gaussian), offline, real-time

Solution

Edge Continuity:

Canny edge detector outperforms others in producing continuous edges.

Noise Sensitivity:

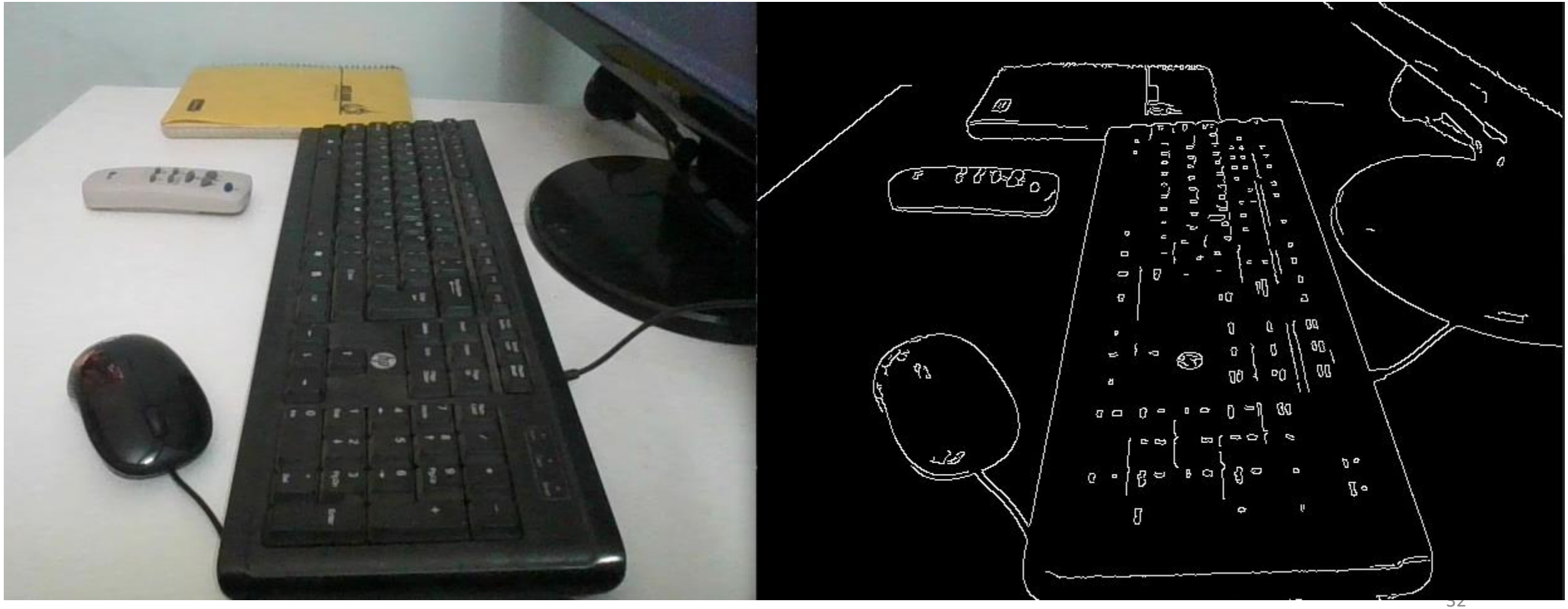
Sobel and Prewitt operators are more sensitive to noise compared to Canny and LoG.

Computational Efficiency:

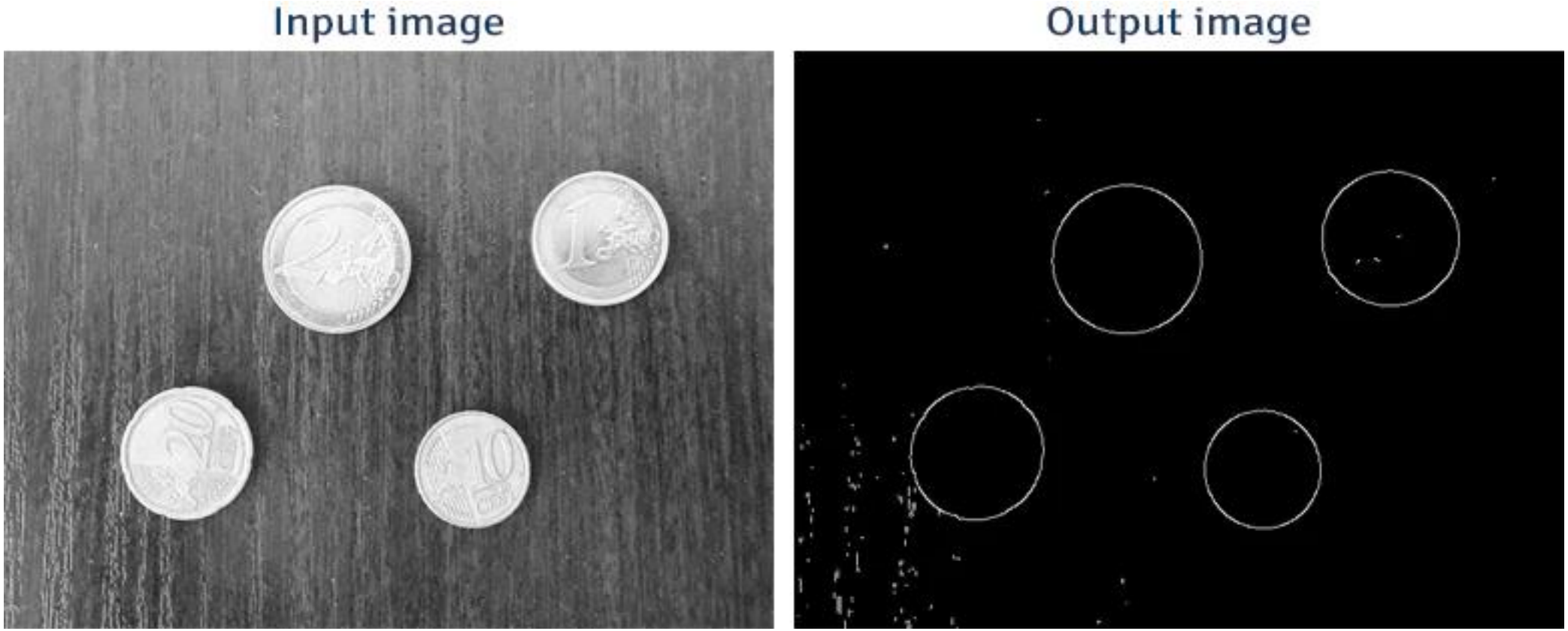
Sobel and Prewitt operators are more efficient, making them suitable for real-time applications.

```
import cv2
import numpy as np
from matplotlib import pyplot as plt

# Step 1: Load the image
image = cv2.imread('sample_image.jpg', cv2.IMREAD_GRAYSCALE)  # Read image in grayscale

# Step 2: Apply Gaussian blur to reduce noise
blurred_image = cv2.GaussianBlur(image, (5, 5), 0)

# Step 3: Apply Canny edge detection
# Parameters:
# - blurred_image: Input image
# - threshold1: Lower threshold for hysteresis procedure
# - threshold2: Upper threshold for hysteresis procedure
edges = cv2.Canny(blurred_image, threshold1=100, threshold2=200)

# Step 4: Display the results
plt.figure(figsize=(10, 5))

# Original image
plt.subplot(1, 2, 1)
plt.imshow(image, cmap='gray')
plt.title('Original Image')
plt.axis('off')

# Edge-detected image
plt.subplot(1, 2, 2)
plt.imshow(edges, cmap='gray')
plt.title('Canny Edge Detection')
plt.axis('off')

plt.show()
```

Canny Edge Detector (Input & Output Image)

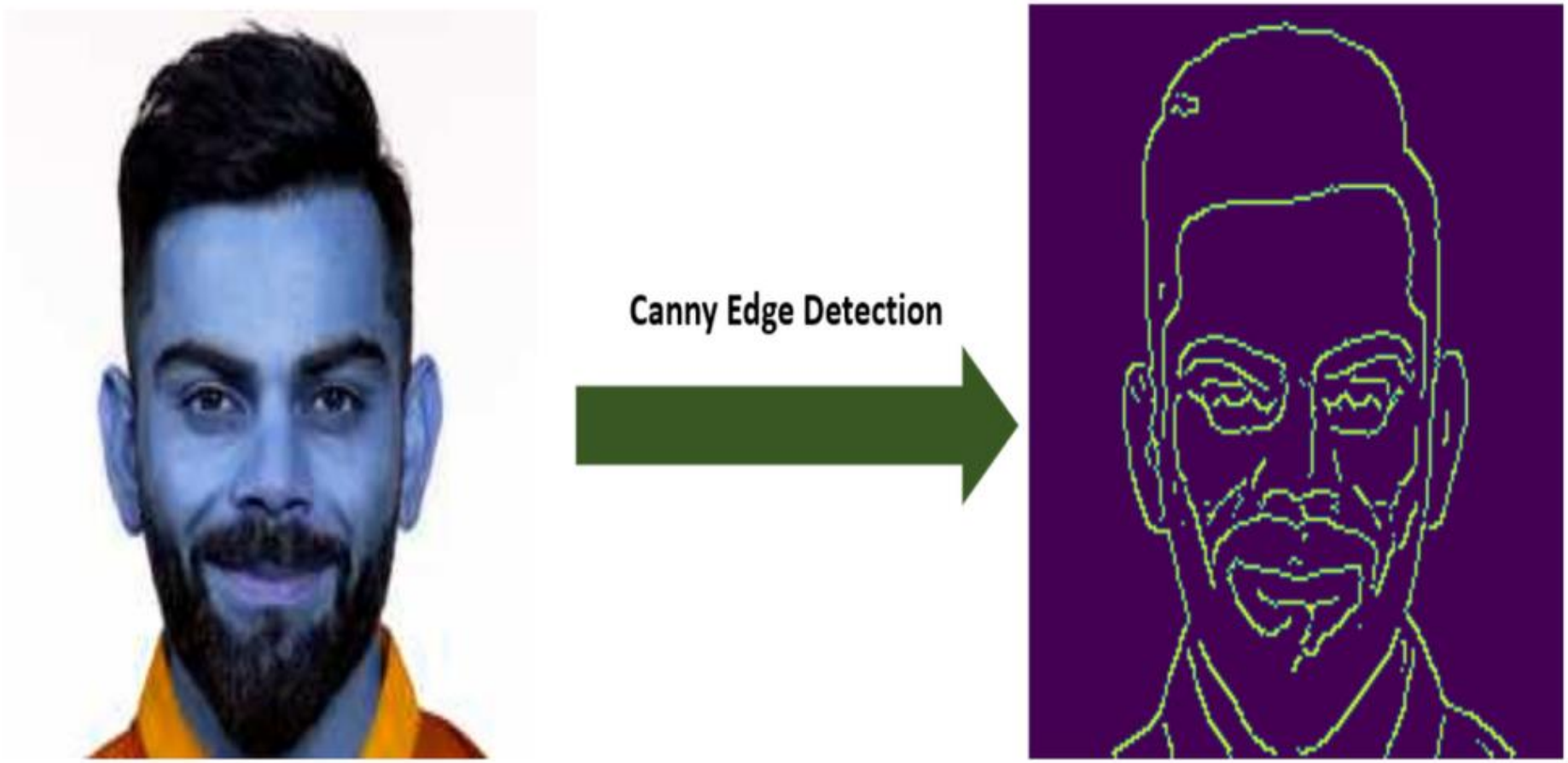


Canny Edge Detector (Input & Output Image)



Canny Edge Detector (Input & Output Image)

Canny Edge Detector (Input & Output Image)



Sobel and Prewitt Filters (cont)

1	2	1
0	0	0
-1	-2	-1

Sobel Horizontal Mask

-1	0	1
-2	0	2
-1	0	1

Sobel VerticalMask

1	1	1
0	0	0
-1	-1	-1

Prewitt Horizontal Mask

-1	0	1
-1	0	1
-1	0	1

Prewitt Vertical Mask

3x3 convolutional Sobel filters:

-1	0	+1
-2	0	+2
-1	0	+1

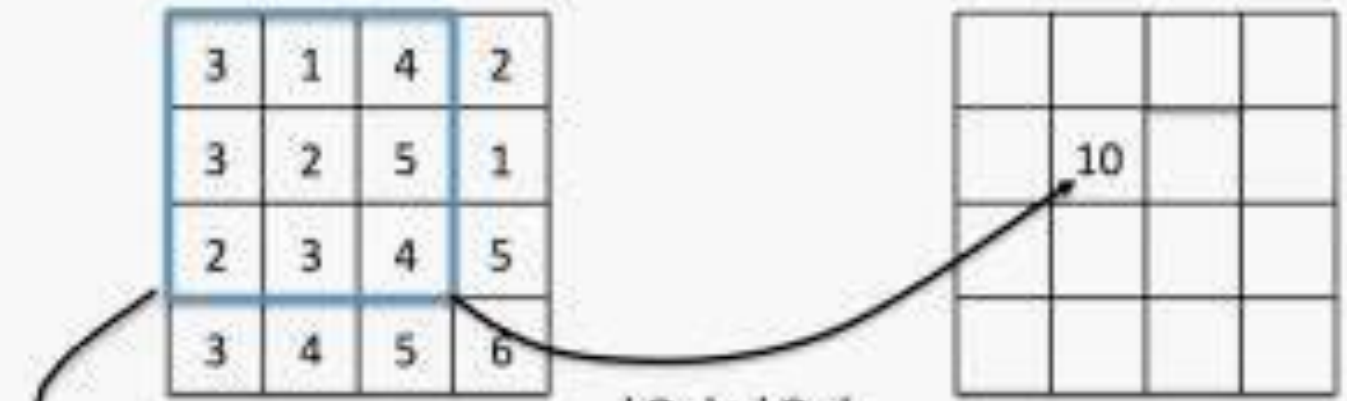
Gx

+1	+2	+1
0	0	0
-1	-2	-1

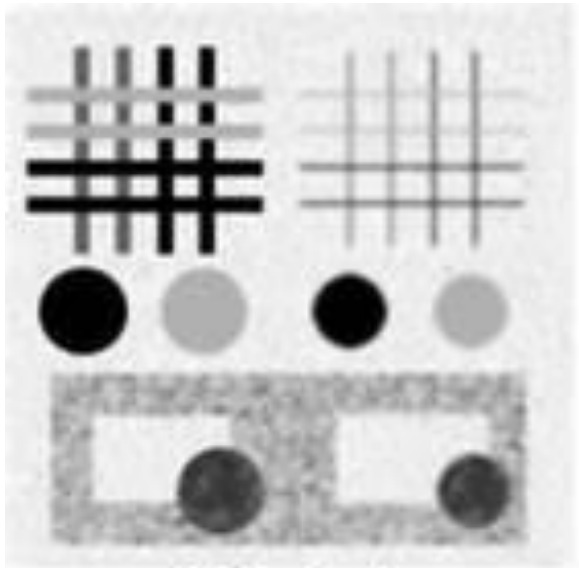
Gy

Gx = (-1*3)+(1*4)+(-2*3)+(2*5)+(-1*2)+(1*4) = 7

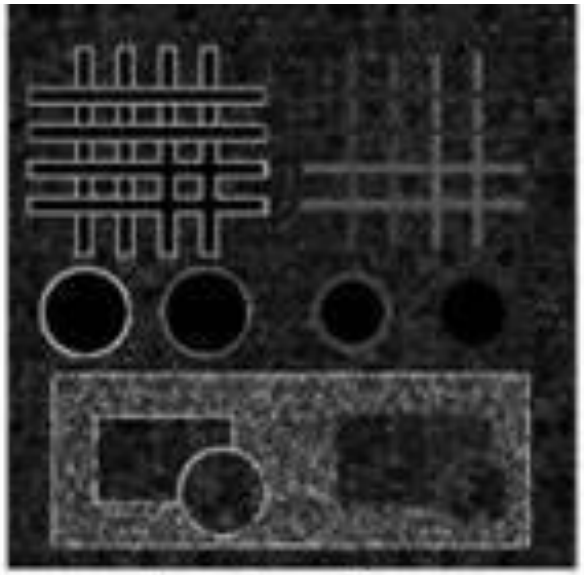
Gy = (1*3)+(2*1)+(1*4)+(-1*2)+(-2*3)+(-1*4) = -3



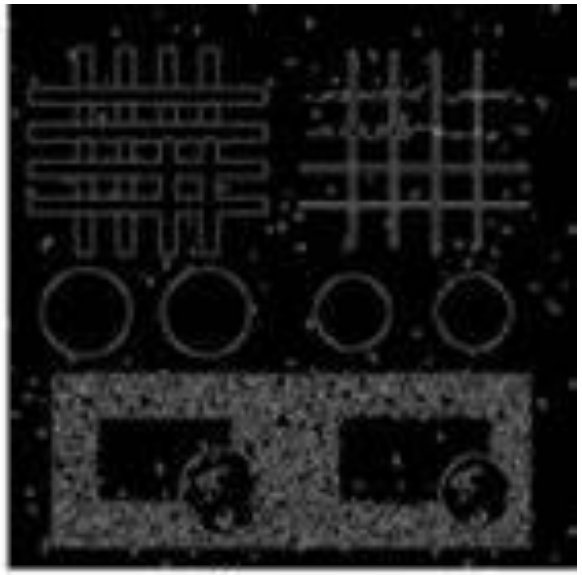
Example "receptive field"



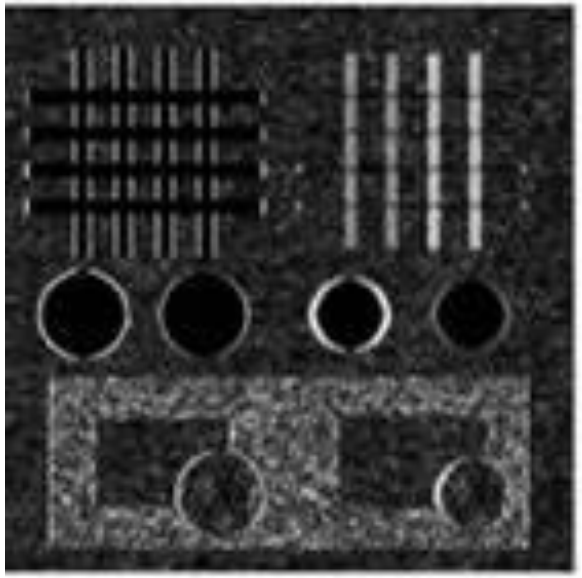
Original



Laplacian

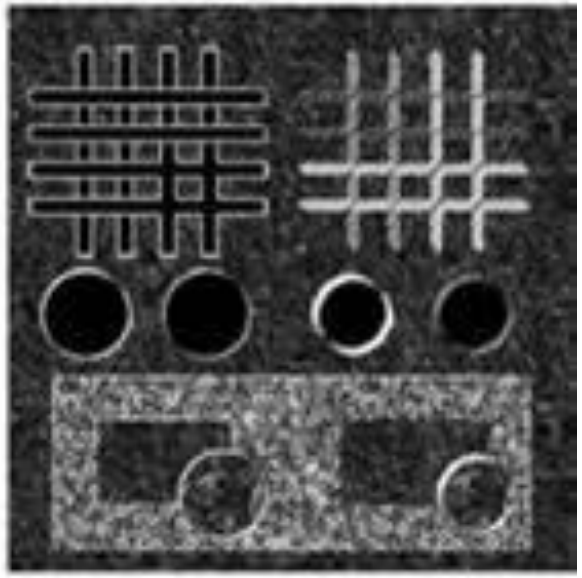


Canny



Sobel X

Sobel Y



Sobel X+Y

processes

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Article

Research on Adaptive Edge Detection Method of Part Images Using Selective Processing

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Abstract: Visual quality inspection of part surfaces is a crucial step in industrial production. Image edge detection is a common technique for assessing the surface conditions of parts. However, current methods have limitations, including poor noise filtering, low adaptability, and inadequate accuracy of edge detection. To overcome these challenges, this study proposes an adaptive edge detection method for part images using selective processing. Firstly, this method divides the input image into noise, edge, and noise-free blocks, followed by selective mixed filtering to remove noise while preserving original image details. Secondly, a four-parameter adaptive selective edge detection algorithm model is constructed, which adaptively adjusts parameter values based on image characteristics to address issues of missing edges and false detections, thereby enhancing the adaptability and accuracy of the method. Moreover, by comparing and adjusting the four parameter values, different edge information can be selectively detected, enabling rapid acquisition of desired edge detection results and improving detection efficiency and flexibility. Experimental results demonstrated that the proposed method outperformed existing classical techniques in both subjective and objective evaluations, maintaining stable detection under varying noise conditions. Thus, this method was validated for its effectiveness and stability, enhancing production efficiency in manufacturing processes of parts.

Keywords: part surface quality inspection; edge detection; mixed filter; adaptive algorithm; selective processing

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1. Introduction

The surface quality of industrial parts is vital in ensuring their safety and stability in subsequent operations. As a result, inspecting the surface quality of parts becomes a critical step in the manufacturing process. Traditional manual inspection methods, however, have drawbacks such as low efficiency, high costs, and a lack of automation [1]. With the continuous advancement of computer technology, machine vision based on image processing techniques has emerged as a superior alternative for part quality inspection, rapidly gaining traction in industrial applications. Specifically, the edge information extracted from images can describe parameters such as part dimensions, orientation, and position, making it a crucial indicator for evaluating part quality [2]. As illustrated in Figure 1, part images contain various types of information, including strong edges, faint edges, false edges, low-frequency information, and slight noise. Among these, the strong edges represent the surface contours and main structural features of the part. Faint edges, which primarily reflect the texture features of the part's surface, present lower contrast and are therefore more challenging to detect. The red box in Figure 1a indicates that due to factors such as uneven lighting, material properties, and slight camera vibrations, banded brightness transition areas may appear on the part's surface. These transitions, clearly visible in the red box of Figure 1b, can be mistakenly identified as edges during detection, despite not being actual edges. Additionally, this type of information exhibits lower contrast compared to faint edges and closely resembles low-frequency information,

processes

MDPI

Article

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Keywords: part surface quality inspection; edge detection; mixed filter; adaptive algorithm; selective processing

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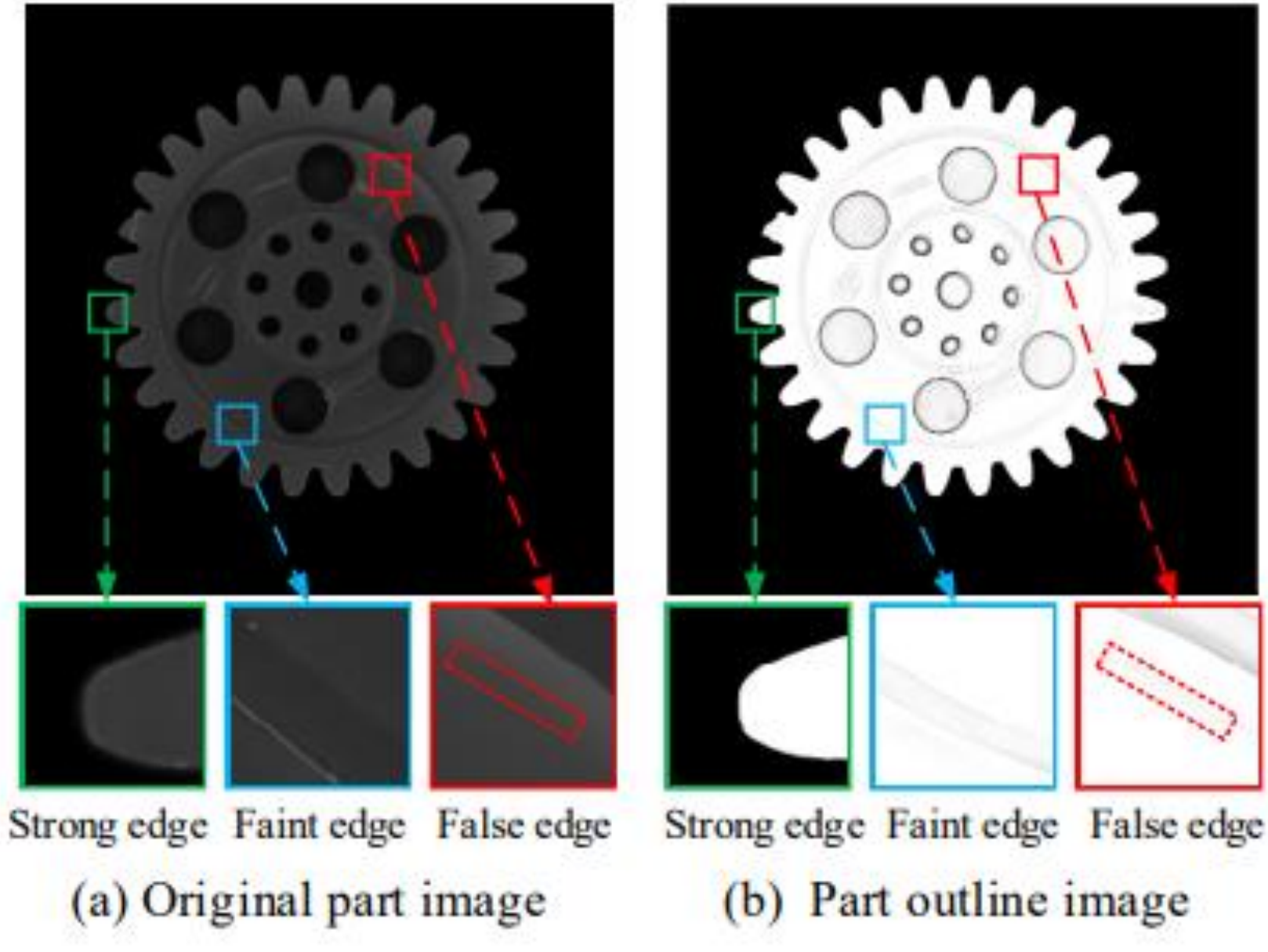


Figure 1. Different edge information features in a part image.

Table 1. Relevant feature information of different edge detection methods.

Classification	Method	Mechanism	Advantages	Limitations
Traditional methods	Robert Sobel Laplacian	Computation of local grayscale values	High detection efficiency	Sensitive to noise
	Canny	Linear filtering to remove noise, considering more factors	Improves edge detection accuracy	Loses feature detail

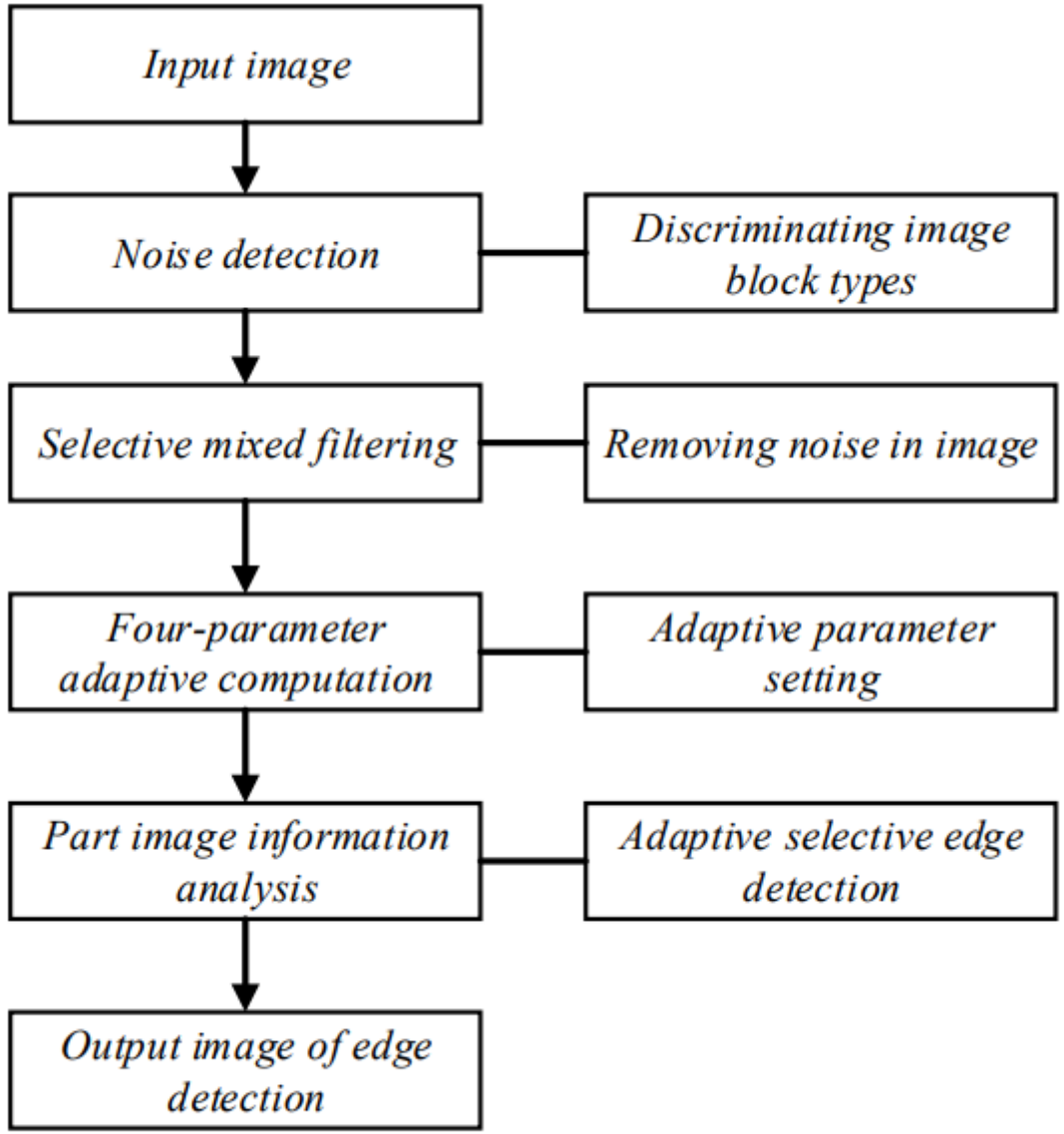


Figure 2. Basic flowchart of the proposed edge detection method.

(a) Original image

(b) Noisy image

(c) Gaussian filter

(d) Median filter

(e) NL-means filter

(f) Liu et al.2023

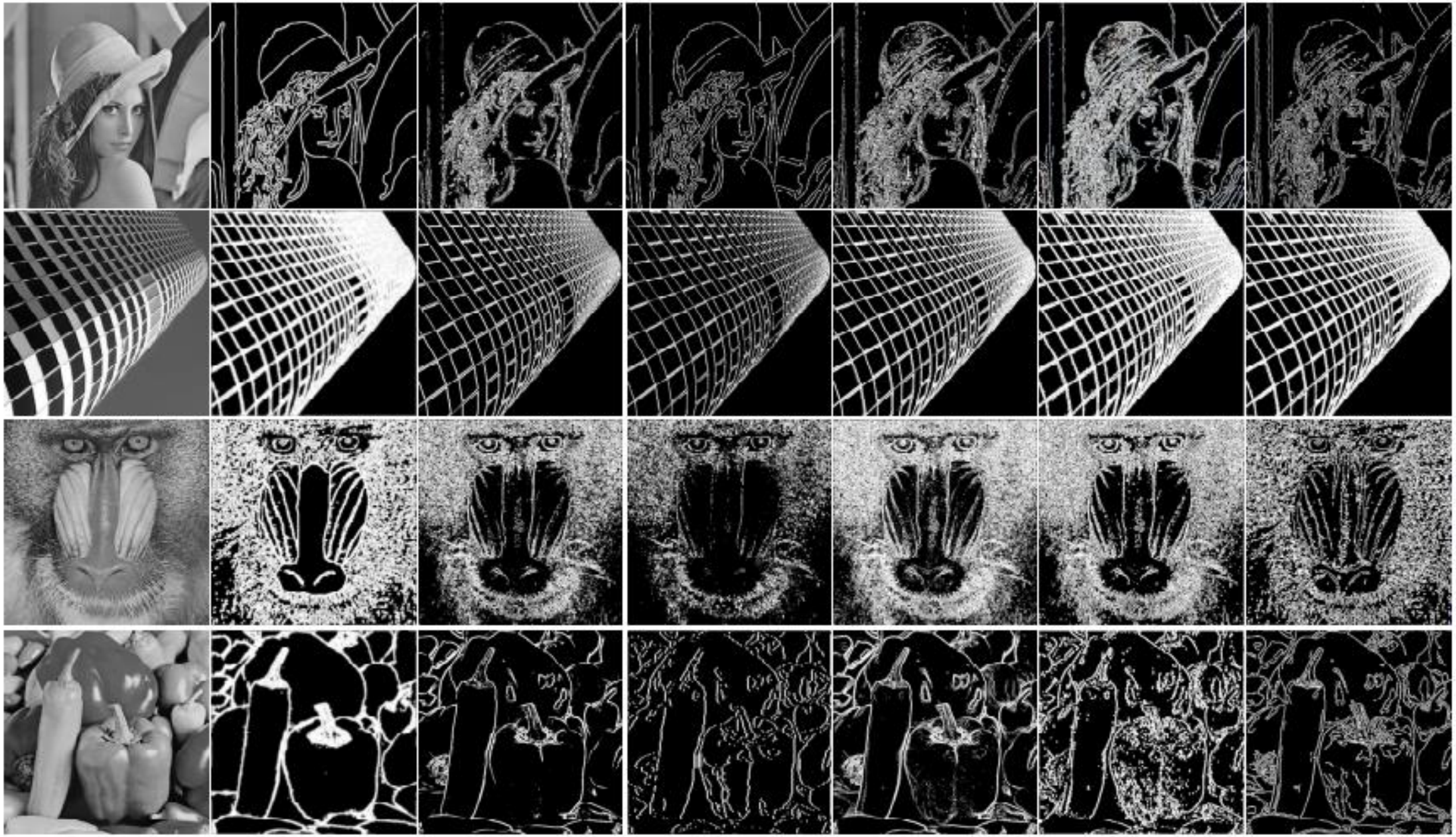
(g) Sun et al.2024

(h) Proposed algorithm

Image	Metrics	Canny	Ref. [11]	Ref. [12]	Ref. [14]	Proposed
Lena	FOM	0.6597	0.7381	0.7798	0.7903	**0.8210**
	F-Measure	0.1449	0.1872	0.1767	0.2399	**0.2457**
Building	FOM	0.7745	0.8466	0.9012	0.8663	**0.9252**
	F-Measure	0.4620	0.5508	0.6312	0.6639	**0.7596**
Baboon	FOM	0.7073	0.8495	0.8895	0.8842	**0.9173**
	F-Measure	0.4027	0.5580	0.7936	0.7318	**0.8891**
Paper	FOM	0.7245	0.7176	0.8369	0.7174	**0.8469**
	F-Measure	0.1327	0.1721	0.2667	**0.3107**	0.3102
Average	FOM	0.7165	0.7879	0.8518	0.8145	**0.8776**
	F-Measure	0.2855	0.3670	0.4670	0.4865	**0.5511**

Note: The bold font in the table indicates that the algorithm achieved the maximum value.

FOM: Figure of Merit



(a) Original image (b) Ground truth (c) Canny (d) Yang et al.2023 (e) Liu et al.2023 (f) Sun et al.2024 (g) Proposed

Table 4. Comparison of the PSNR, SSIM, FOM, and F-Measure obtained from different edge detection methods under mixed noise conditions $\sigma = 0.3$ and $\rho = 0.2$.

Image	Metrics	Canny	Ref. [11]	Ref. [12]	Ref. [14]	Proposed
Lena	PSNR	18.50	27.85	28.77	29.31	**31.84**
	SSIM	0.4704	0.7220	0.7769	0.8263	**0.8594**
	FOM	0.4997	0.7198	0.7552	0.7309	**0.8197**
	F-Measure	0.1068	0.1665	0.1686	0.2102	**0.2312**
Building	PSNR	20.56	25.56	27.09	28.13	**29.02**
	SSIM	0.2122	0.6065	0.7562	0.7982	**0.8126**
	FOM	0.7245	0.8045	0.8214	0.8412	**0.9012**
	F-Measure	0.3142	0.4234	0.5135	0.6364	**0.6594**
Baboon	PSNR	20.99	28.89	27.54	**30.27**	30.05
	SSIM	0.6032	0.8620	0.8226	0.8599	**0.9026**
	FOM	0.4073	0.8195	0.8462	0.8652	**0.9023**
	F-Measure	0.1970	0.2187	0.6533	0.6282	**0.7937**
Paper	PSNR	18.80	26.44	27.66	29.75	**33.34**
	SSIM	0.1196	0.6539	0.7412	0.7965	**0.8433**
	FOM	0.5545	0.6869	0.8151	0.7145	**0.8245**
	F-Measure	0.1084	0.1388	0.2080	0.2872	**0.3050**
Average	PSNR	19.71	27.19	27.77	29.37	**31.06**
	SSIM	0.3514	0.7111	0.7742	0.8202	**0.8545**
	FOM	0.5465	0.7576	0.8094	0.7879	**0.8720**
	F-Measure	0.1816	0.2368	0.3858	0.4405	**0.4973**

Note: The bold font in the table indicates that the algorithm achieved the maximum value.

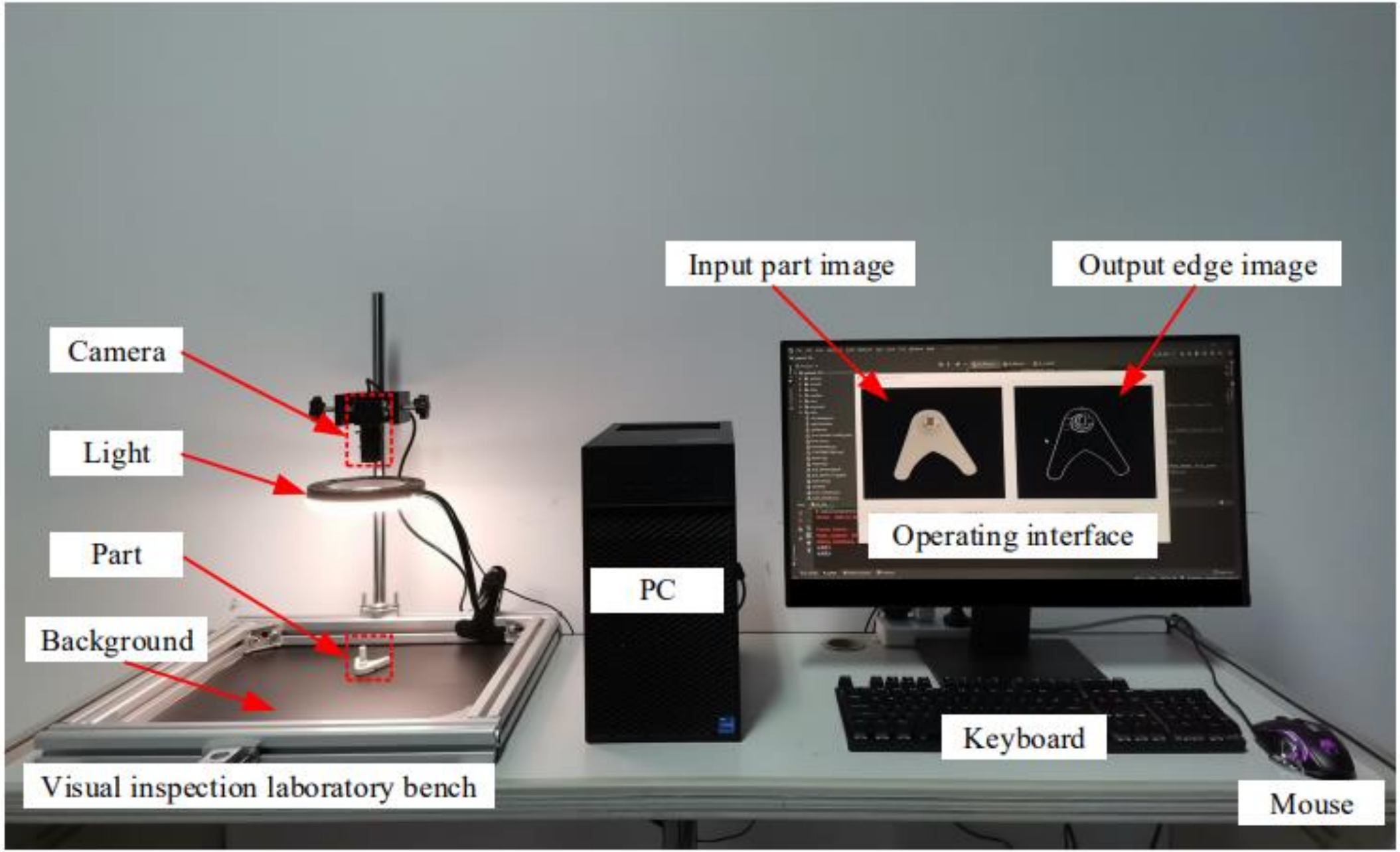
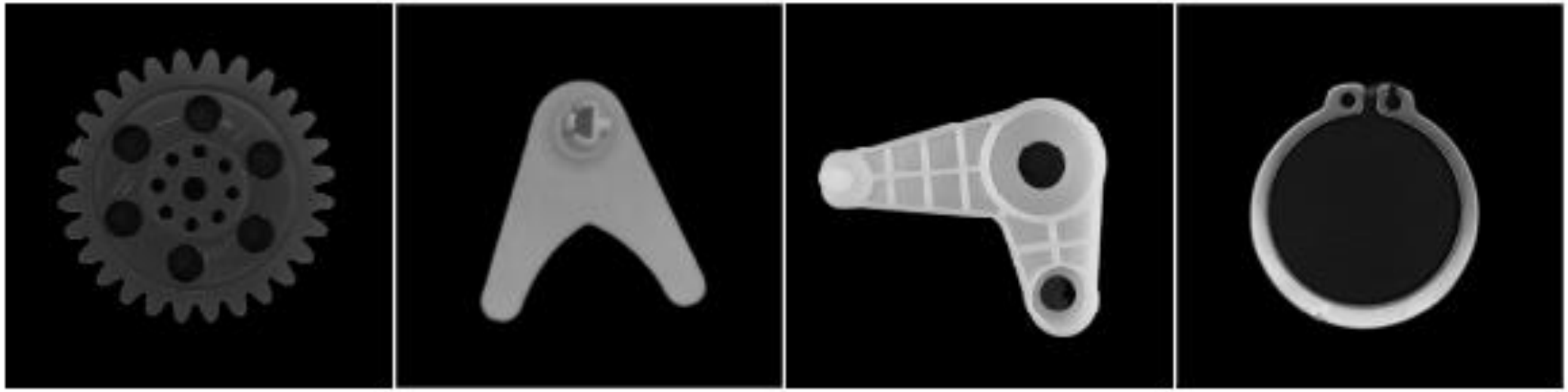
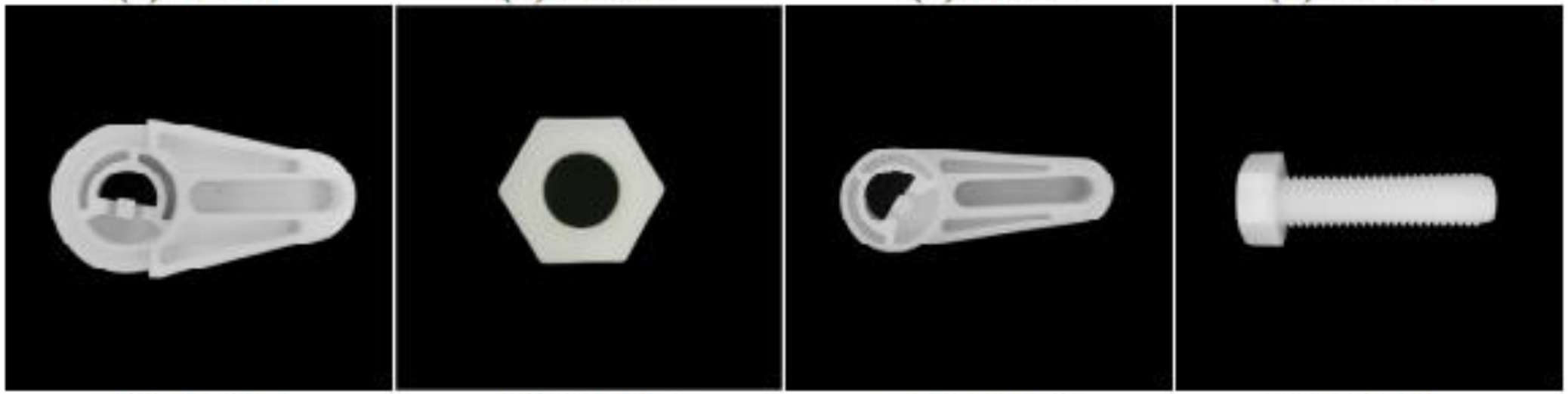


Figure 9. Part surface quality inspection experimental platform.

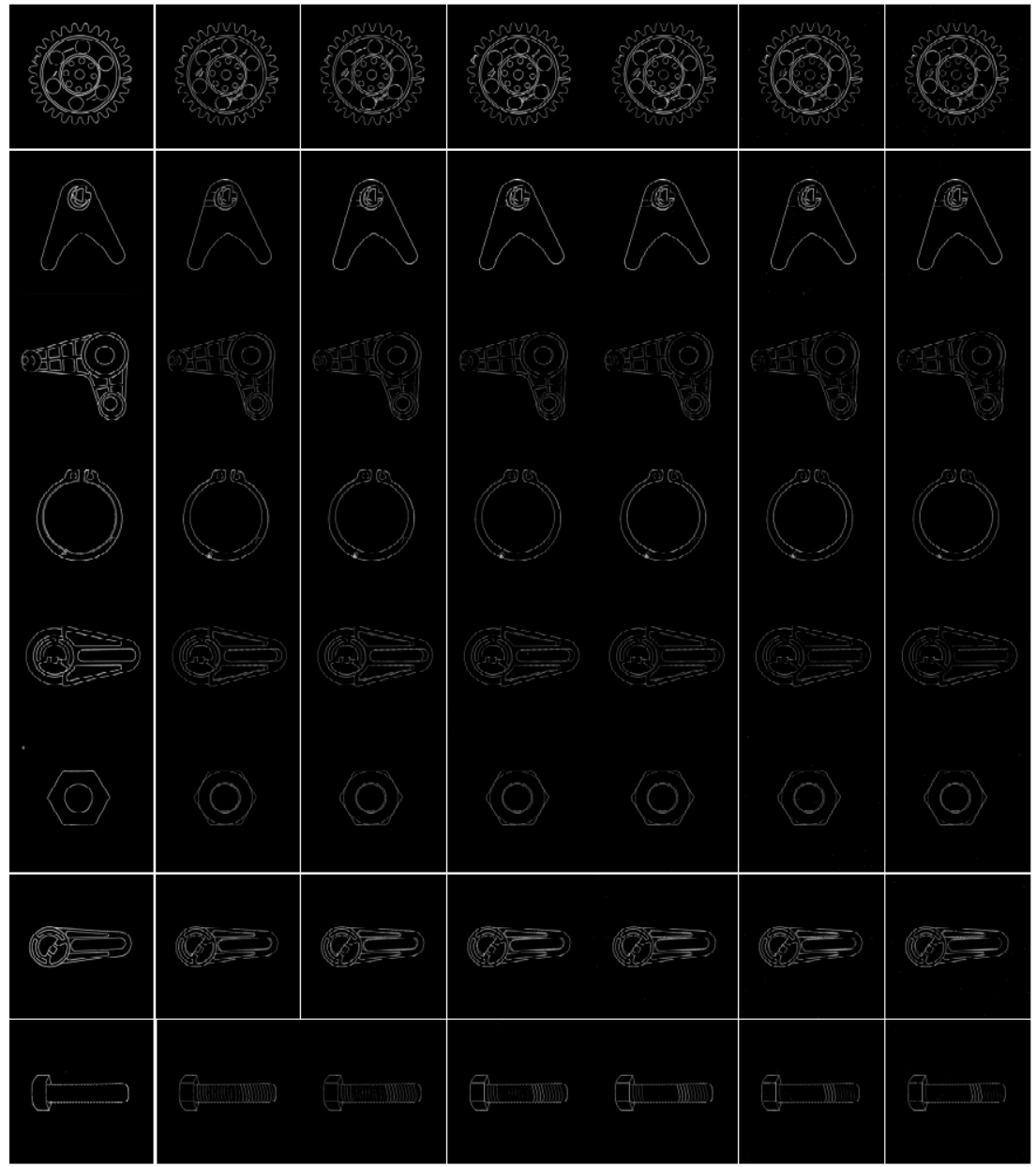


(a) Part 1 (b) Part 2 (c) Part 3 (d) Part 4



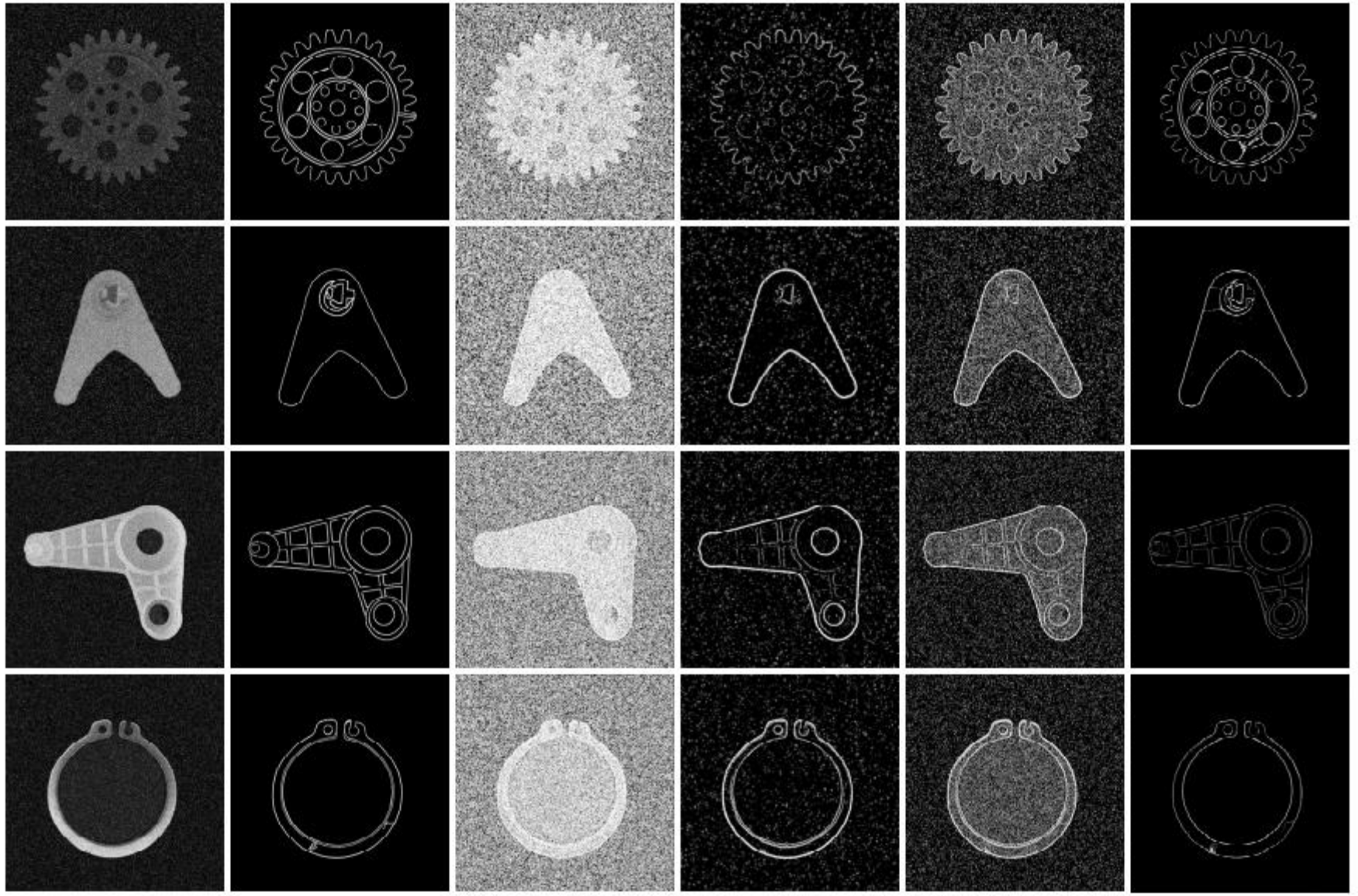
(e) Part 5 (f) Part 6 (g) Part 7 (h) Part 8

Figure 10. Part images collected by the camera.



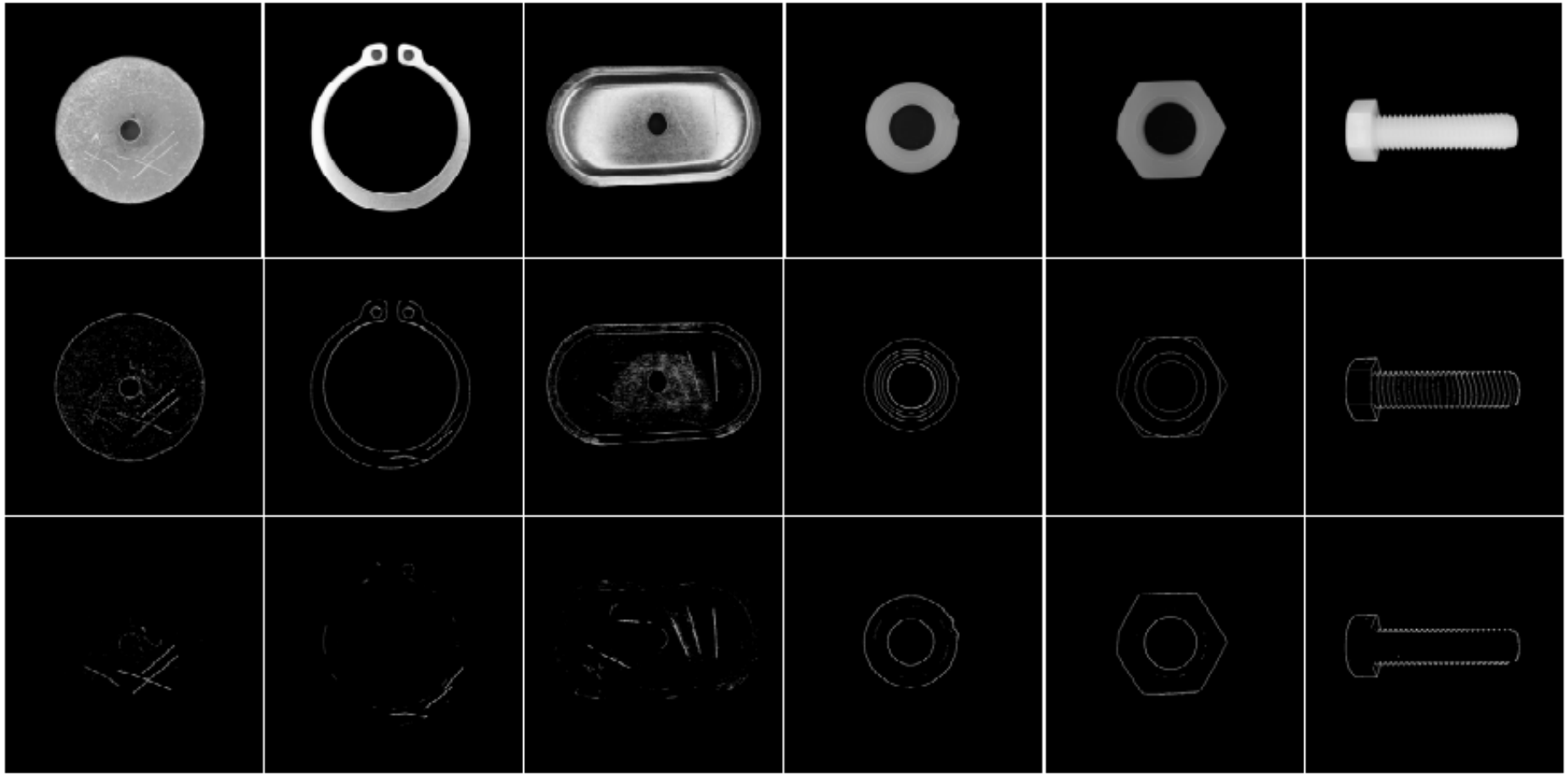
(a) Ground truth (b) Noise-free (c) $\sigma, \rho = 0.1$ (d) $\sigma, \rho = 0.2$ (e) $\sigma, \rho = 0.3$ (f) $\sigma, \rho = 0.4$ (g) $\sigma, \rho = 0.5$

Figure 11. The subjective results of edge detection for each part image under noise-free and mixed noise conditions.



(a) Noisy image (b) Ground truth (c) Sobel (d) Canny (e) Liu et al.2023 (f) Proposed

Figure 12. Comparison of t the detection results of different edge detection methods for part under mixed noise conditions with $\sigma,\rho = 0.3$ [12].



(a) Part 1 (b) Part 2 (c) Part 3 (d) Part 4 (e) Part 5 (f) Part 6

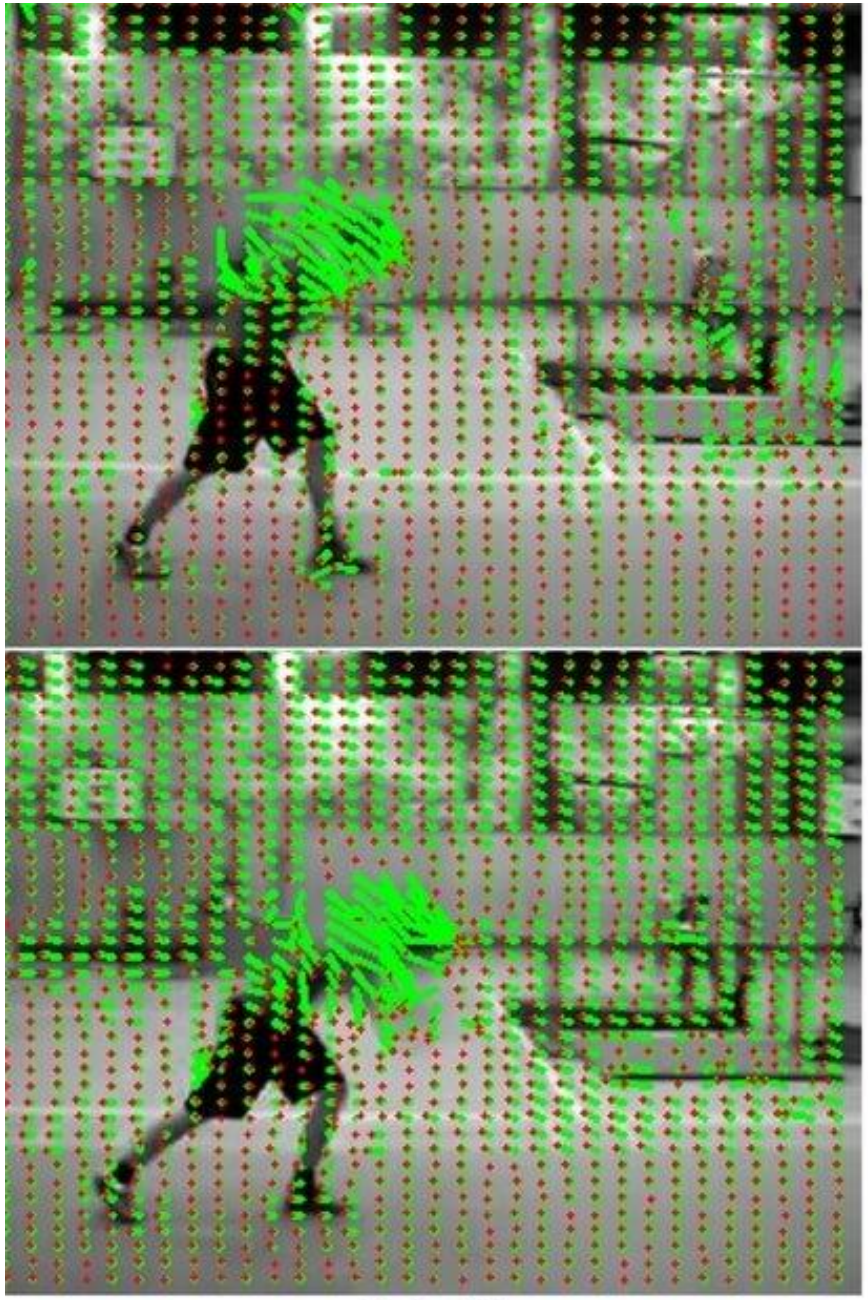
Figure 13. Comparison of integrity and selective edge detection results on different part images.

Noise Removal from Moving Sequence of Images

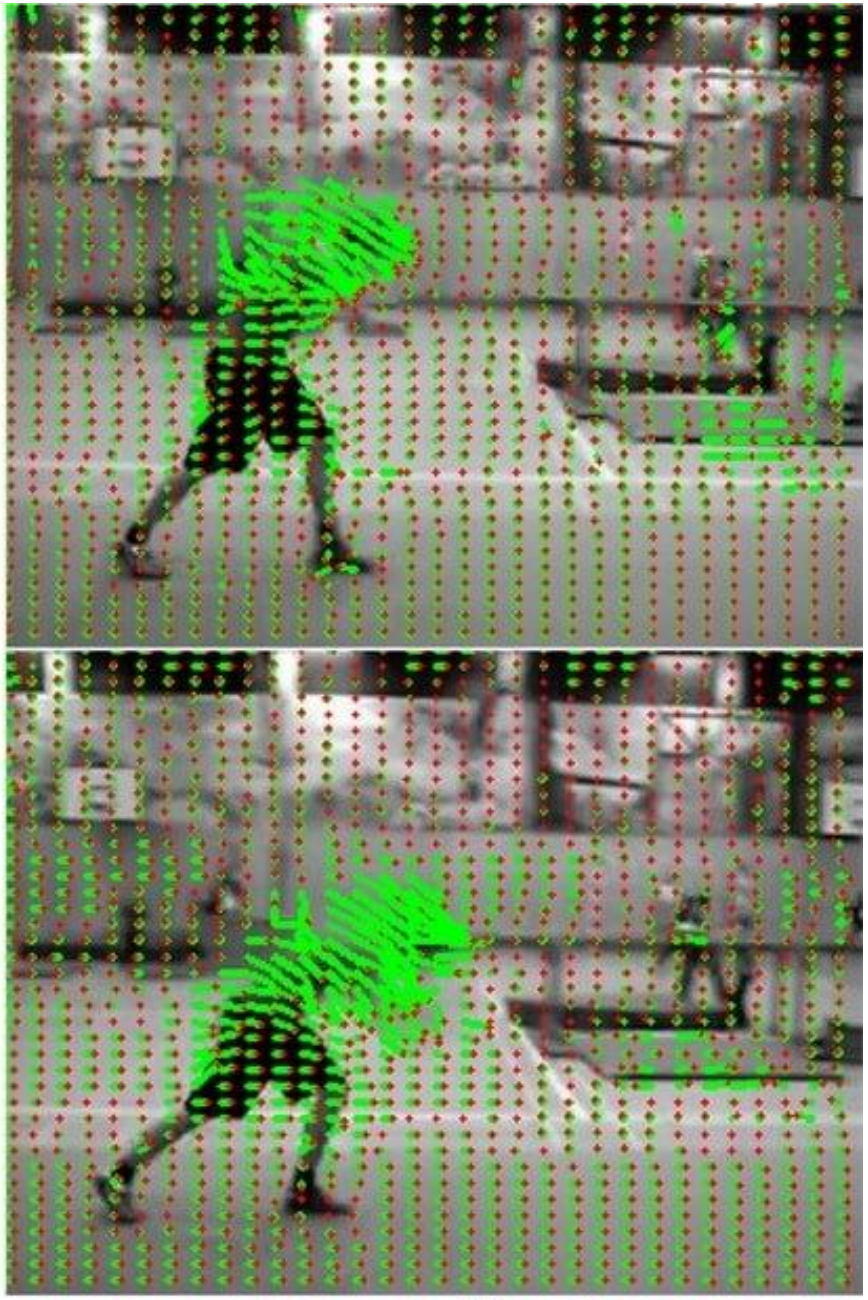
- Program

Noise Removal from Moving Sequence of Images

1. **Temporal Averaging**
   - **Principle**: If the noise is random and varies from frame to frame, averaging multiple frames can reduce the noise while preserving the underlying image content.
   - **Method**:
     - Align the frames to account for motion (using optical flow or feature matching).
     - Average the pixel values across the aligned frames.
   - **Limitation**: This method works best for static scenes or when the motion is minimal.



Optical flow vectors



Compensated flow vectors

Noise Removal from Moving Sequence of Images

2. Spatial Filtering

- **Principle**: Apply spatial filters to each frame to reduce noise.
- **Common Filters**:
  - **Gaussian Blur**: Smooths the image, reducing high-frequency noise.
  - **Median Filter**: Effective for removing salt-and-pepper noise.
  - **Bilateral Filter**: Reduces noise while preserving edges.
- **Limitation**: Spatial filtering can blur fine details and edges.

Noise Removal from Moving Sequence of Images

3. Temporal Filtering

- **Principle**: Apply filters across the temporal dimension (i.e., across frames).
- **Common Filters**:
  - **Kalman Filter**: Useful for estimating the true state of a pixel over time.
  - **Wiener Filter**: Optimal for reducing noise when the signal and noise characteristics are known.
- **Limitation**: Requires accurate motion estimation and can be computationally intensive.

Factors Kalman Filter Considers :

Future Target position can be calculated based on newtons law:

$$x = x_0 + v_0\Delta t + \frac{1}{2}a\Delta t^2$$

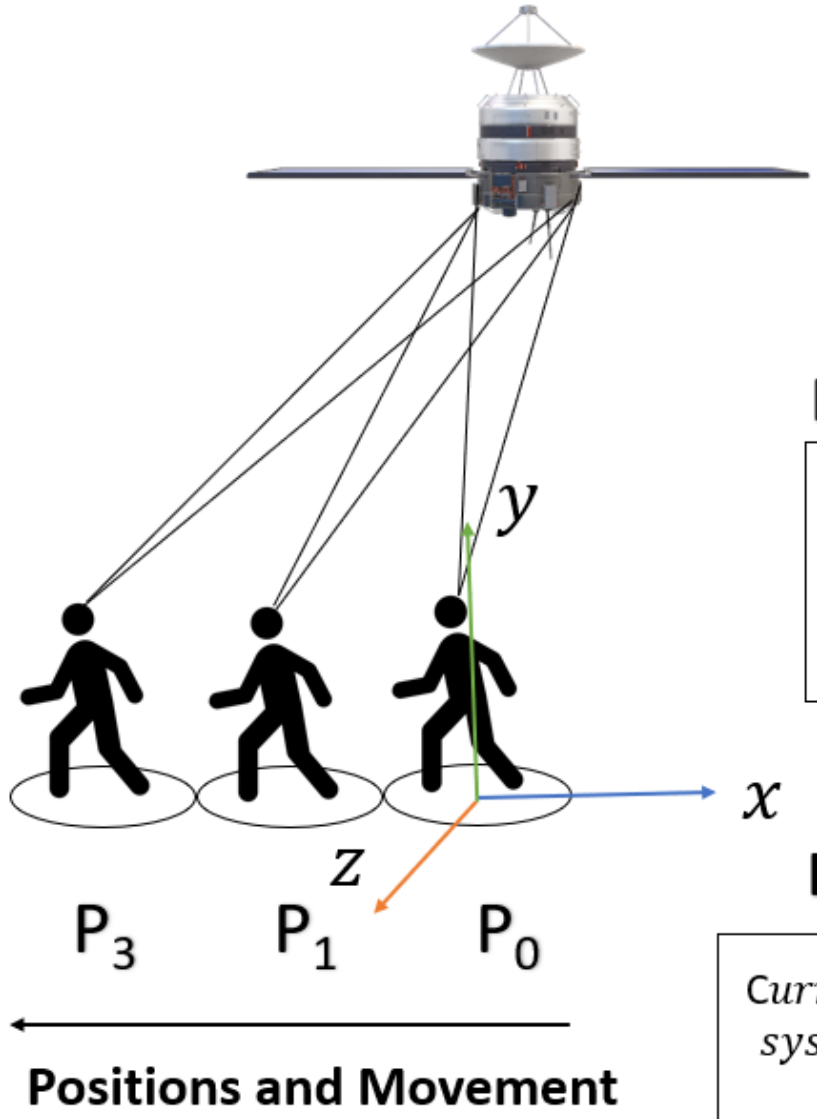
Where x is future target position,x0 is initial target position, v0 initial velocity, Δt time interval

In 3D system :

$$\begin{pmatrix} x = x_0 + v_x\Delta t + \frac{1}{2}a_x\Delta t^2 \\ y = y_0 + v_y\Delta t + \frac{1}{2}a_y\Delta t^2 \\ z = z_0 + v_z\Delta t + \frac{1}{2}a_z\Delta t^2 \end{pmatrix}$$

System State

$$x, y, z, v_x, v_y, v_z, a_x, a_y, a_z$$



Process Noise

Target motion is not strictly aligned with motion evaluation due to wind, temperature etc.

Measurement Noise

GPS sensor in watch is not calibrated properly.

Dynamic System

Current state is the input to the systemnext state is output of the algorithm.

Noise Removal from Moving Sequence of Images

4. Motion Compensation

- **Principle**: Compensate for motion to align frames before applying temporal filtering.
- **Method**:
  - Estimate motion between frames using optical flow or block matching.
  - Warp frames to align them.
  - Apply temporal filtering on the aligned frames.
- **Limitation**: Accurate motion estimation is crucial and can be challenging in complex scenes.

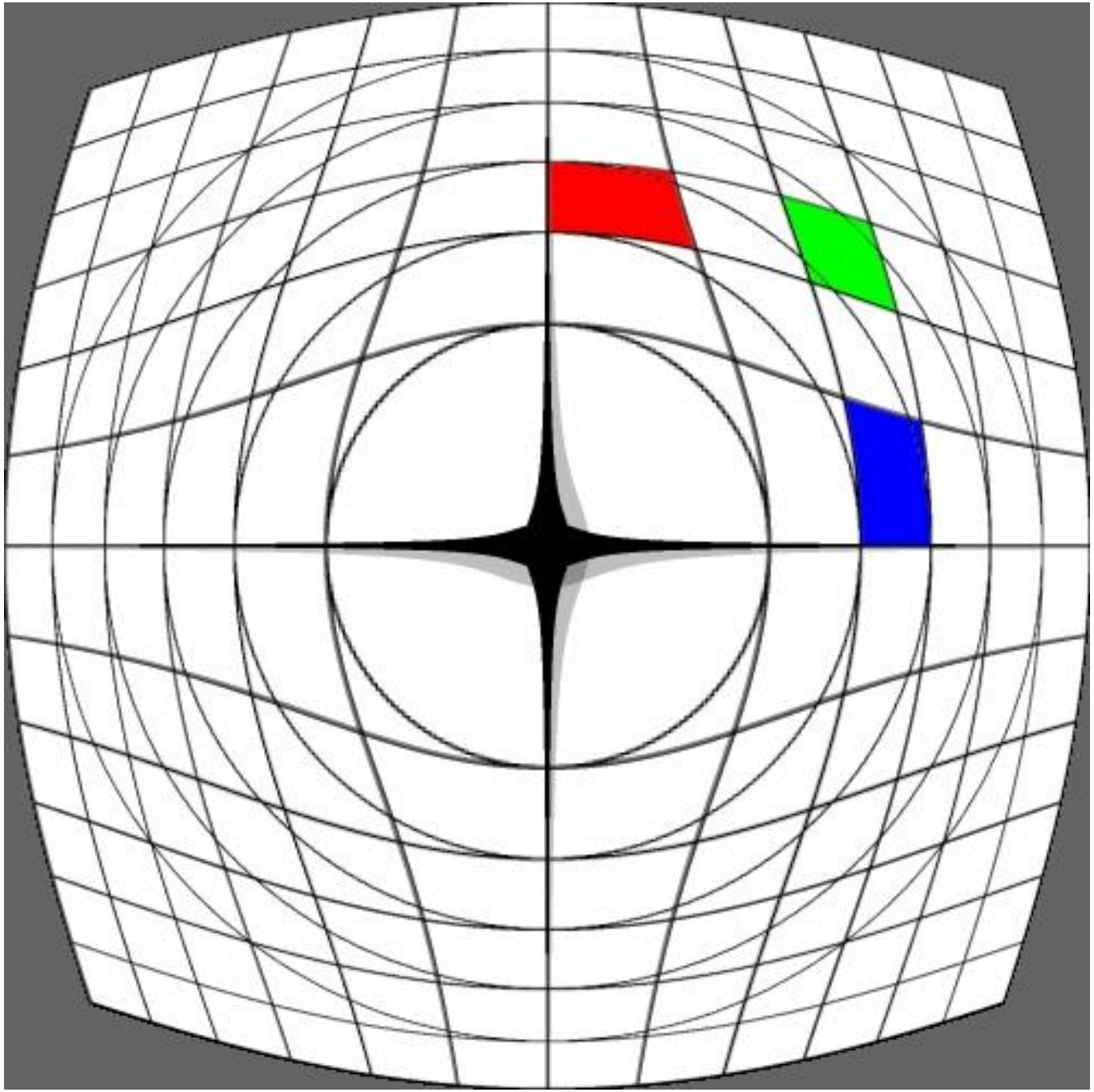
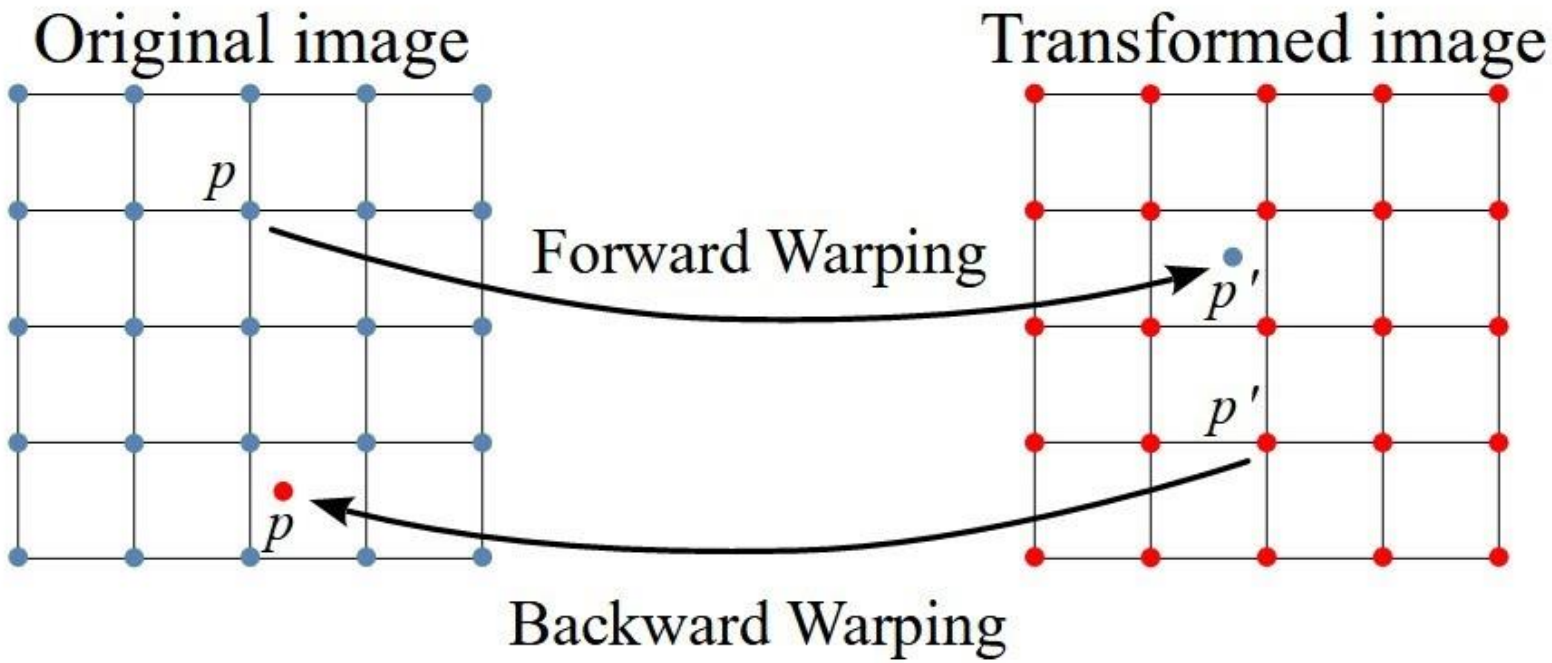


Image Warping

FORWARD AND BACKWARD IMAGE WARPING

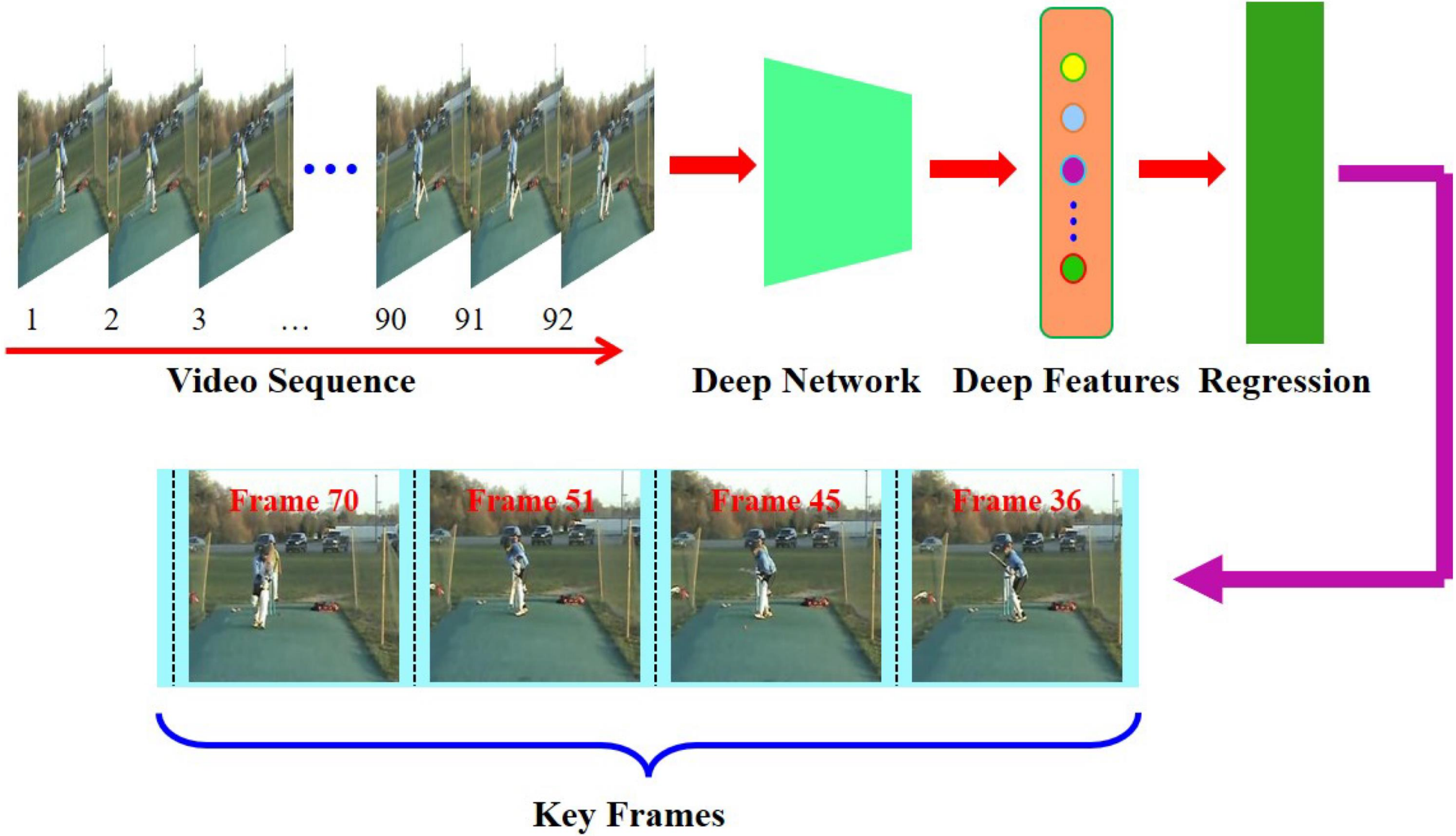


Vertical wave
Horizontal wave
Multidirectional wave
Concave

Noise Removal from Moving Sequence of Images

5. Machine Learning-Based Methods

- **Principle**: Use trained models to separate noise from the image content.
- **Common Techniques**:
  - **Convolutional Neural Networks (CNNs)**: Train a CNN to denoise images.
  - **Autoencoders**: Use an autoencoder to learn a noise-free representation of the images.
- **Limitation**: Requires a large dataset for training and significant computational resources.


1
2
3
…
90
91
92
Video Sequence
Deep Network
Deep Features
Regression
Frame 70
Frame 51
Frame 45
Frame 36
Key Frames

Take-Home Examination (5 Marks)

Indigenous with own data set

Home Assignment-H1

Posted 10:48 AM

1) Write the Problem Statement
2) Compare the state of the art (available best algorithms) functionality and performance
3) Craft a new problem statement with solution of the problem surrounding your work area(s)
4) Presentation to be given on the first day of class after Ramadan Break

Edge Detection Paper-...

PDF